

MEMRISTORS – A NEW ERA OF ARTIFICIAL INTELLIGENCE

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Today, artificial intelligence has penetrated almost all spheres of our life. The pace of development of neural networks continues and is only increasing, creating a kind of ‘neural network boom’.

Today neural networks are actively used for scientific purposes to process and analyse huge amounts of data, but larger and more complex neural networks require more and more complex and voluminous computations, requiring a significant increase in computing power.

The vast majority of computing systems today are based on the von Neumann architecture, whereby the processor that performs the computation is connected to memory via a bus, thus creating a bottleneck, the so-called ‘Bottle Neck’ of the von Neumann architecture.

For the work and creation of neural networks such a bottleneck is critically important, due to the fact that their training requires the processing of huge amounts of memory, which due to the separate location of the computing device and memory block can not be transferred efficiently enough [1].

The use of architecturally conventional computers for the creation and operation of neural networks is still justified, because such a rapid introduction of artificial intelligence began relatively recently, but future generations of neural networks can hardly work efficiently even on the existing supercomputers.

The problem with this need for such cumbersome and costly computations is that today neural networks are not directly created in the physical sense, but only emulated in software, which means that many resources are spent on side calculations.

Thus, creating ever larger neural networks requires more and more computational effort, which in turn leads to greater energy requirements.

The solution to these problems may be the use of a new electronic component, the memristor. The theoretical basis of the memristor was outlined in 1971 by Chinese professor Leon Chua in his paper ‘Memristor-The Missing Circuit Element’.

According to this paper, the four basic circuit variables: current, voltage, charge and flux-coupling can be related in six possible ways. For two of these ways there are physical laws, and for the other three there are basic circuit elements: a resistor is the relationship between v and i , an inductance is the relationship between ϕ and i , and a capacitor is the relationship between q and v . However, a sixth relation between ϕ and q was missing [2].

To fix such a slender picture, Chua just decided to add a memristor. It was not until 2008 that a prototype element was created that was similar in properties to the theoretically described memristor, but was not.

Nevertheless, the sample created then became known as a memristor, although it did not reflect some theoretical properties (the laboratory sample did not operate based on magnetic flux) [3].

Memristors, being the fourth basic element of electrical circuits, have properties that make them promising for applications in neural networks and artificial intelligence.

One of the key characteristics of memristors is their ability to remember the previous resistance state, which allows them to perform computation and data storage in the same element, thus eliminating the ‘bottle neck’ of the von Neumann architecture.

Thanks to their ability to change resistance depending on the current flowing through them, memristors can simulate the synapse behaviour of biological neural networks.

This makes them ideal candidates for creating energy-efficient and compact neuromorphic processors that can perform parallel computations and learn on a hardware level similar to the human brain.

Because memristors store a resistance value (analog value), they can be used in neural networks to implement analog calculations, which allows for significantly higher accuracy of information processing compared to traditional digital methods.

This is especially important for tasks that require working with fuzzy and noisy data, such as pattern recognition, image processing, and natural language analysis.

One of the most promising applications of memristors is the development of specialized neuromorphic chips in which memristors replace traditional transistors and RAM.

Such systems can significantly speed up data processing, reduce power consumption, and improve the efficiency of neural network training [4].

For example, research is already underway on the use of memristor arrays in processors capable of real-time learning without the need to access external memory [5].

To date, there is active research in the field of memristor fabrication based on various materials, including transition metal oxides, polymer compounds and two-dimensional nanostructures.

One of the key directions is the development of energy-efficient and reliable memristors that can maintain their state for a long time and operate under high load conditions.

This makes the memristor one of the most promising areas in the development of hardware for artificial intelligence.

Their introduction may lead to the creation of new generations of computing systems that will significantly surpass existing technologies in terms of both performance and energy efficiency, opening a new era in the development of artificial intelligence.

References

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