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NEUROMORPHIC COMPUTING

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ABSTRACT

Neuromorphic computing promises to improve energy efficiency by an order of magnitude compared to the traditional von Neumann computing paradigm. The aim is to develop an adaptive, fault-tolerant, space-saving, fast and energy-efficient intelligent system by learning and imitating brain functions, which can be achieved through innovations at various levels of abstraction, including materials, devices, circuits, architecture and algorithm. This summary discusses the fundamental concepts, applications, and implications of neuromorphic computing. Unlike traditional von Neumann architectures, neuromorphic systems aim to mimic the parallel processing, fault tolerance, and energy efficiency of biological neural networks. Based on neuroscientific principles, these systems integrate hardware and software to emulate synaptic connections, enabling the development of intelligent machines capable of learning, adapting and performing complex cognitive tasks.

Keywords: Neuromorphic Computing, Von Neumann Architecture, Human Brain Functionality, Energy-Efficient Computing Spiking Neural Network, Artificial Intelligence, ANN.

[I] INTRODUCTION

Neuromorphic computing, a technology that mimics neurobiological architectures in the nervous system via electronic circuits, is gaining traction as next-generation computing due to its ability to process complex data with high efficiency, high speed, and low power consumption. The importance of neuromorphic computing in the industry has increased as AI algorithms execute it efficiently by mimicking the neural structure of the human brain. Traditional von Neumann calculations with separate processors and memory systems are not effective for machine learning due to processor and memory bottlenecks. Since machine learning requires a special amount of work to data, there should be enormous traffic between processors and memory. In the case of a neuromorphic computing system, it consists of many neurons and synapses to calculate and store data, as well as a neural network to transmit this data. Therefore, this computer system can efficiently calculate simple iterations for machine learning training. This chapter discusses the goals and challenges of neuromorphic computing

and shows how research into the development of materials, devices, and algorithms raises great expectations in field of neuromorphic computing.

[II] LIMITATION OF VON NEUMANN ARCHITECTURE

The von Neumann architecture, which is the basis for most modern computers, has been highly successful, but it is not without its problems and limitations. Here are some of the problems and challenges related to von Neumann architecture:

- Memory Hierarchy: The von Neumann architecture has a hierarchical memory structure, with different levels of caches and main memory. This hierarchy can lead to bottlenecks as data must be moved between these levels, which can slow down computation.
- Sequential Execution: In a von Neumann architecture, instructions are executed sequentially, one after another. This can limit performance, especially for tasks that require massive parallelism.
- Energy Inefficiency: The constant data movement between memory and the CPU, as well as the clocking of the CPU, can result in high power consumption. This is a significant issue for mobile devices and data centers.
- Limited Parallelism: Von Neumann architectures are not inherently designed for parallel processing. Exploiting parallelism often requires complex programming and can be inefficient.
- Data Transfer: Transferring data between different components of the system (e.g., CPU, memory, storage) can be a bottleneck and result in significant overhead.
- Latency: High latency in accessing data from memory can lead to reduced performance, especially for applications that rely on fast data retrieval.
- Scalability: Scaling up the performance of von Neumann architecture-based systems can be challenging, as it may require increasing clock speeds, which can lead to heat and power issues.
- Data-Centric Workloads: With the growth of data-centric applications, such as AI and big data analytics, von Neumann architectures can struggle to efficiently handle large datasets due to memory access bottlenecks.

[III] NEUROMORPHIC ARCHITECTURE

Neuromorphic architecture represents a paradigm shift in computing inspired by the structure and function of the human brain. It involves the design of hardware and software systems that mimic the neural processing capabilities of biological brains. At its core are simplified models of neurons and synapses, which perform computations and communicate via spikes or pulses of activity. Unlike traditional computing architectures, neuromorphic systems operate in an event-driven manner, where computations are triggered by neural events rather than by a central clock. This approach offers advantages in terms of efficiency, parallelism, and low power consumption. Neuromorphic architecture holds promise for a wide range of applications, including pattern recognition, sensory processing, and adaptive control, where its ability to process complex information in real-time with minimal energy expenditure is particularly advantageous. Ongoing research and development in this field continue to refine and expand the capabilities of neuromorphic computing, paving the way for the next generation of intelligent systems.

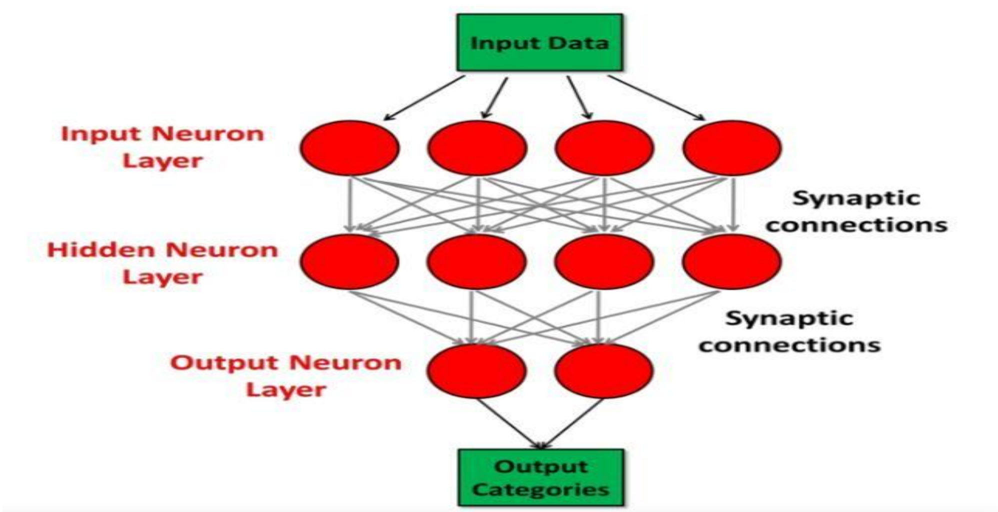

Fig 3.1 Neuromorphic Architecture

[IV] METHODS AND ALGORITHMS

A) Spike-Based Quasi-Backpropagation

Neuromorphic computer architecture aims to mimic the structure and functionality of the human brain. One such approach that is taken in training SNNs for neuromorphic hardware is to directly adapt the training procedure to produce an SNN rather than an ANN. In this case, the typical training procedures of backpropagation or stochastic gradient descent are modified so that they will produce an SNN suitable for hardware deployment. SpikeProp pioneered a bespoke gradient descent approach for spiking neural networks, specifically focused on first-spike times as a proxy for the neuron's output value and applying a process similar to traditional gradient descent.

In an approach for training binary-activated networks suitable for hardware deployment is presented. This approach, called Whetstone, begins with differentiable activation functions such as sigmoid or RELU and gradually "sharpens" those functions over the course of training to behave like binary activation functions that are suitable for neuromorphic deployment. Several approaches have adapted back-propagation by using a surrogate gradient. One such approach for training both the spatial and temporal aspects of SNNs. In this adaptation for

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traditional back-propagation by maintaining an approximated derivative of spike activity throughout.

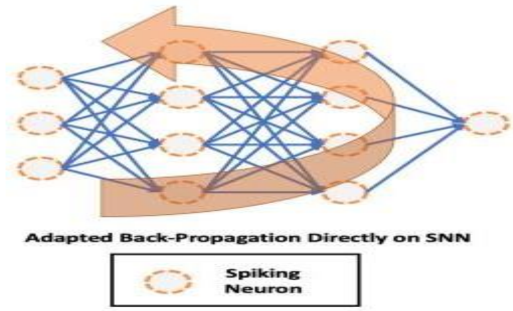

Fig 4.1 Spike-based quasi-backpropagation approaches adapt backpropagation to work directly onSNNs

B) Mapping Traditional ANNs to SNNs:

One of the common approaches used in the field is to train a traditional artificial neural network (ANN) and then create a mapping from that ANN to an SNN for neuromorphic hardware deployment.

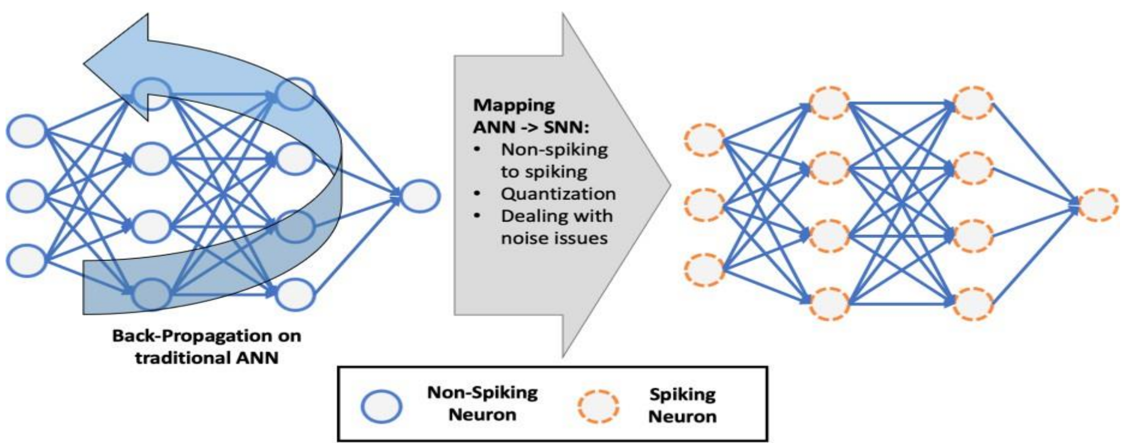

Fig 4.2 Mapping Traditional ANNs to SNNs

[V] NEUROMORPHIC APPLICATIONS

1. Medicine

The ability of neuromorphic devices to receive and process information from the

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environment is particularly effective. These devices can work with the human body in combination with organic components. Neuromorphic devices could improve drug delivery techniques in the future.

2. **Large-scale operations and product customization**

Neuromorphic computing can also be useful for large-scale initiatives and product adaptations. This would enable faster processing of huge amounts of data from environmental sensors. Depending on industry requirements, these sensors can monitor water content, temperature, radiation and other properties.

3. **Artificial Intelligence**

By definition, the goal of neuromorphic computing is to reproduce the way the human brain works. Neuron in the brain receive, process and transmit impulses very quickly and energy efficiently. It is therefore logical that technology experts, especially in the field of artificial intelligence (AI), are fascinated by this type of data processing.

4. **Imaging**

Just as the human eye creates images, neuromorphic vision sensors do the same. These are event-based imaging devices. This shows that they produce images in response to light intensity, which is an external rather than an internal signal. They also move faster regardless of the traditional frame rate. In a neuromorphic sensor, each pixel functions independently of its neighbours.

[VI] NEUROMORPHIC COMPUTING GOALS

Neuromorphic computing aims to achieve several goals, drawing inspiration from the

in emulating certain aspects of neural processing, achieving a complete replication of the human brain's complexity remains a long-term goal. Current neuromorphic models are more specialized and focused on specific tasks.

• Mimic the brain's remarkable energy efficiency, where neurons perform complex computations with significantly lower power consumption compared to traditional computing architectures.

• Enable real-time processing of sensory data and decision-making, reducing latency and enabling quick responses in applications such as robotics, autonomous systems, and edge computing.

• Emulate cognitive functionalities, including learning, adaptation, and pattern recognition, to create machines that can perform tasks with human-like intelligence.

• Leverage parallelism and distributed processing to handle multiple tasks simultaneously, improving overall system efficiency and computational throughput.

• Design specialized hardware components, such as memristors and neuromorphic chips, to support the unique requirements of neuromorphic computing.

[VII] CONCLUSION

Although neuromorphic devices have promising properties, they still present several challenges that need to be addressed to realize energy-efficient neuromorphic systems. Neuromorphic computing technology has raised great expectations and its market volume is increasing every day in various fields. Neuromorphic computing holds promise as a transformative approach to data processing and draws inspiration from the complex architecture and functionality of the human brain. In the coming years, there will likely be additional discoveries and applications that will advance the broader landscape of artificial intelligence and cognitive computing.

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