Neuromorphic Computing

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Abstract: Neuromorphic computing represents a cutting-edge approach to computer engineering, inspired by the architecture and functionality of the human brain and nervous system. Unlike traditional computing paradigms, neuromorphic computing seeks to emulate the parallel processing and distributed memory capabilities of biological neural networks.

The need for neuromorphic computing arises from inherent limitations in conventional computing architectures, such as the von Neumann design. In traditional systems, memory and computation are segregated, requiring data to be transferred between memory and the central processing unit (CPU) via a bus. However, the speed of memory access and data transfer has not kept pace with the increasing performance of CPUs, leading to inefficiencies known as the von Neumann bottleneck and the computation-memory gap.

Neuromorphic computing addresses these challenges by adopting a fundamentally different approach. Inspired by the brain's ability to process information in parallel and store data locally within neurons, neuromorphic systems utilize artificial neurons that communicate through electric signals, or spikes. This enables them to perform computations and store information simultaneously, without the need for separate memory and processing units.

Key components of neuromorphic computing include artificial neurons, which mimic the behavior of biological neurons, and electric spikes, which serve as the means of communication between neurons. By leveraging the principles of the nervous system, neuromorphic computing offers the potential for enhanced efficiency, scalability, and performance, particularly in tasks involving large-scale data processing and pattern recognition.

Keywords: Neuromorphic Computing, Artificial Neurons, Electric Signals, Electric Spikes, Nervous System, Computation.

Introduction

Computer components are modelled after the human nerve and brain systems in a process known as neuromorphic computing. The phrase refers to both the programme and hardware components of computers.

The fastest computation rates are made possible by neuromorphic computers by doing away with the need for bulky hardware and specialised structures. Neuromorphic engineers draw on a range of disciplines, including computer science, biology, mathematics, electronic engineering, and physics, to build artificial neural systems that are motivated by biological architecture.

Neuromorphic computing combines cutting-edge hardware development, materials science, and concepts from neuroscience with computing disciplines like machine learning and artificial intelligence.

The term "neuromorphic" was first applied to specialised hardware/chips that incorporated analogue components and replicated organic neural activity. Today, the field of neuromorphic computing has expanded to encompass a wide range of hardware and software components as well as study in materials science, neuroscience, and computational neuroscience.

However, in the majority of cases, the term "neuromorphic computing systems" refers to equipment with the following characteristics:

- co-located memory and computation,
- two fundamental components: neurons and synapses,
- Simple component-to-component exchange,
- Internal component learning

Additional features that some neuromorphic systems (though not all) have;

- Nonlinear dynamics,
- strong fan-in/fan-out components,
- nonlinear dynamics,
- Spiking behaviour,
- plasticity of both factors for adaptation and learning, robustness and
- the capacity to deal with noisy or erroneous input are all desirable characteristics.

With input from neurophysiologists, computational neuroscientists, biologists, computer scientists, device engineers, circuit designers, and material scientists, the community must address a large numberof design decisions given the broad range of characteristics of neuromorphic systems.

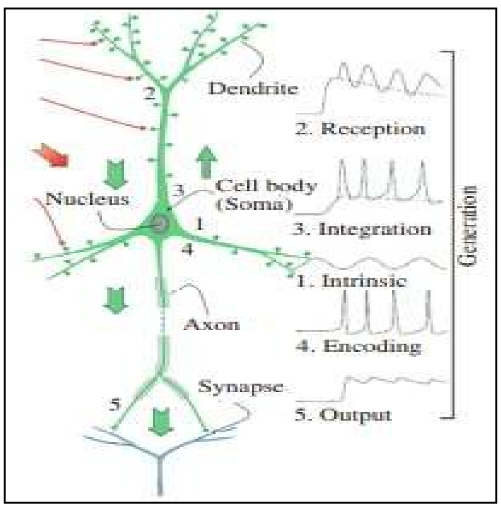

Fig.1.1 structure of neuron & synapse

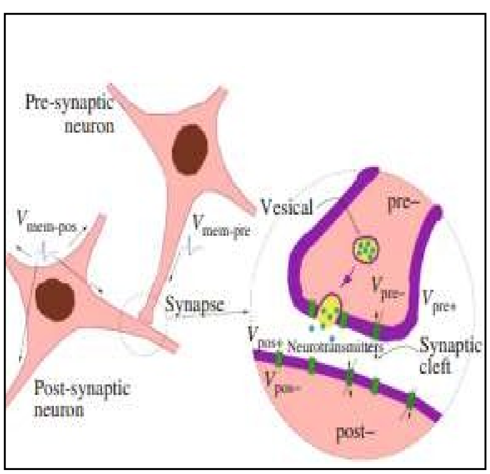

Fig.1.2 structure of neuron & synapse

Hardware for simulating the brain:- Neuromorphic systems

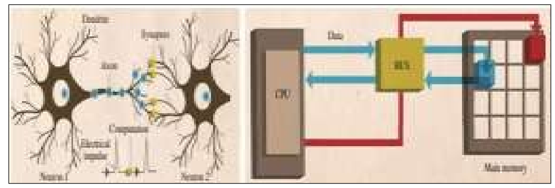

Fig.2 The brain's synapses, which are junctions where neurons can communicate and retainmemory in the form of connection strength, are the brain's computing architecture and a centralprocessing unit (CPU) connected to the primary memory unit by a bus in a conventional computerarchitecture.

Even the biggest and fastest supercomputers in the world cannot compare to the overall processing power of the human brain in performing many tasks, such as pattern recognition, perception, motor control, flexibility in changing environments, learning, and ultimately, intelligent cognition. Supercomputers can store more information than the human brain and can compute equations more quickly. However, they still dwarf human brains in size and energy consumption by a factor of a million.

It is very alluring to research the structure and functioning processes of the brain in order to mimic it using electronic circuits because of the brain's incredible capabilities. A novel type of computer architecture known as neuromorphic architecture has been created as a result of research into the human brain and the computing systems it inspired. To create artificial neural systems, this field combines knowledge from various fields, including biology, physics, mathematics, computer science, and engineering [12]. These artificial nervous systems' physical architecture and design concepts are founded on those of biological nervous systems.

The behaviour and connections between neurons can be partly simulated on a conventional computer, but due to the fundamental differences between these two systems, such a system will consume excessive power and is unable to utilise the brain's architecture. There is now a race to create new gadgets and hardware architectures that more closely approach bio-intelligent systems at the physical level and effectively mimic the functioning of the brain. The so-called neuromorphic circuit, for instance, is composed of components that act like neurons and communicate and process information by sending spikes rather than constantly varying voltages. Carver Mead created the idea of neuromorphic engineering in the late 1980s. Mead defined it as "mimicking neurobiological architectures found in the nervous system using VLSI systems incorporating electronic analogue circuits."

Methodologies

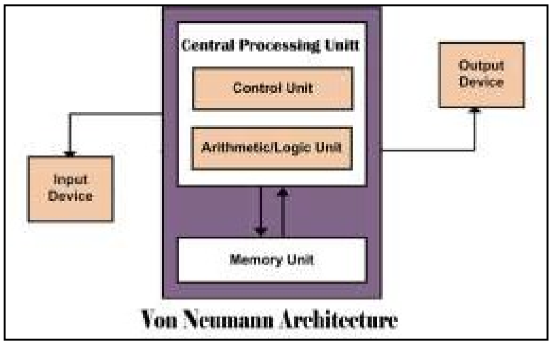

Fig 3: Von Neumann Architecture

Memory and computation are separated by a bus in the von Neumann design, and data for the current programme as well as the programme itself must be transferred from memory to a central processing unit (CPU). Memory access and transfer speeds have not increased at the same rate as CPU performance increases. While the von Neumann bottleneck and the computation-memory divide are causing problems at the same time, we are collecting.

Backus provided an explanation of the von Neumann barrier. Neuromorphic Computing Architectures, Models, and Applications 6 There must be a less archaic method than squeezing a huge volume of words back and forth through the von Neumann bottleneck to implement significant changes in the store. This tube is not only a literal bottleneck for the data traffic of an issue, but, more significantly, it is an intellectual bottleneck that has restricted our ability to think in terms of the larger conceptual units of the task at hand and instead kept us bound to word-at-a-time thinking. Programming is essentially the organizing and organization of the massive word flow through the von Neumann bottleneck, much of which is concerned with finding important data rather than the data itself.

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Furthermore, Moore's law, which states that the number of transistors on a chip double approximately every two years, is starting to slow. As a result, even CPU performance gains are slowing (if not plateau). Though there is debate over whether Moore's law has actually been broken, it is generally agreed that Dennard scaling, which states that power density remains constant as transistors get smaller, came to an end around 2004. As a result, energy usage on chips has risen as transistor count has grown. We are collecting more data than ever before, despite the von Neumann bottleneck, the computation-memory gap, the peak of Moore's law, and the end of Dennard scaling all occurring at the same time.

Data is collected in enormous quantities and in a variety of formats using a wide range of techniques, including sensors in actual environments, by businesses, groups, and governments, as well as from scientific instruments or simulations. Because of the limitations of the available processing resources and related algorithms, a large portion of this data is stored inactively, summarized for researchers using statistical methods, or is simply discarded. In addition, as computing has advanced, the kinds of problems that we as users want computers to handle have expanded beyond needs for intelligent data analysis. We specifically anticipate increasingly intelligent conduct from our systems.

Non-von Neumann designs have been developed as a result of these problems and others. In particular, the objective of researching novel architectures is not to discover a substitute for the conventional von Neumann paradigm, but rather to discover architectures and gadgets that can enhance the current paradigm and assist in addressing some of its shortcomings. One of the suggested complement architectures is neuromorphic, and for good cause.

Communication expenses can be decreased by colocating memory and computation and by using straightforward communication between components. Often, neuromorphic architectures have reduced power requirements (which can be a result of analogue or mixed analog-digital devices or due to the event-driven nature of the systems). On neuromorphic devices, common data processing methods like neural networks are easily implemented.

Uses, models, and architectures of neuromorphic computing;

There is a chance that intelligent behaviour will develop if the design is constructed using brain-inspired components.3 In comparison to current architecture, neuromorphic computing has the ability to significantly improve computational efficiency in areas like big data analysis, sensory fusion and processing, real-world/real-time controls (such as robots), cyber security, etc. These apps will be verypoorly supported without neuromorphic computing as a component of the future computing landscape. This report's objectives are to outline a road map for the computing community's potential efforts to address some of the most important open research issues related to the computing component of neuromorphic computing. By computing, we mean those elements of neuromorphic computing that have more to do with architecture, software, and applications than those that are more concerned with devices and materials. A roundtable on neuromorphic computing: from materials to systems architecture, organised by the DOE and conducted in October 2015, preceded this workshop.

The ASCR and BES offices of the Office of Science jointly sponsored the roundtable, which featured computer scientists, device engineers, and materials scientists and stressed the value of an interdisciplinary approach to neuromorphic computing. The significance of working in conjunction with device engineers, circuit designers, neuroscientists, and materials scientists is stressed even though this report is written explicitly from the perspective of computing.

Algorithms/ Techniques

The installation of Artificial Neural Networks (ANN), which are made up of millions of artificial neurons, is the first step in the operation of devices that support neuromorphic computing. These neurons resemble those found in the human brain.

- ✓ Layers of these artificial neurons send signals to one another, enabling a machine (computer) to behave and function like the human brain. Neuromorphic computing devices function by converting input into an output through electric signals or electric spikes.
- ✓ Spiking Neural Networks serve as the foundation for the transmission of electric spikes or messages (SNN). An artificial machine can operate like a human being and mimic brain activity thanks to this spiking neural network architecture.
- ✓ This may entail duties like data interpretation and visual recognition, among many others. In comparison to conventional computers, neuromorphic computing devices are low power consumers because they only use power when electric spikes are transmitted through them.
- ✓ Neuromorphic computing devices mimic the neuro-biological networks found in the human brain to function just like a human brain and carry out tasks quickly and accurately.
- ✓ However, computers based on neuromorphic computing use a lot less room and have the ability to perform tasks more effectively and quickly.

Applications

Fig. 4 Prosthetic Arm Surgery

Medical

The ability of neuromorphic devices to receive and process information from their surroundings is very strong. These devices can work with the human organism when combined with organic materials.

Neuromorphic devices may enhance medication delivery techniques in the future. Due to their high responsiveness, they could release a drug when they noticed a shift in the body's conditions (i.e., varying insulin and glucose levels).

The use of neuromorphic computing technology in prostheses is also possible. Another advantage of this technology is their capability to effectively receive and process an external signal. For people withprostheses, using neuromorphic devices rather than conventional ones could result in a more natural, seamless experience.

Large scale operations

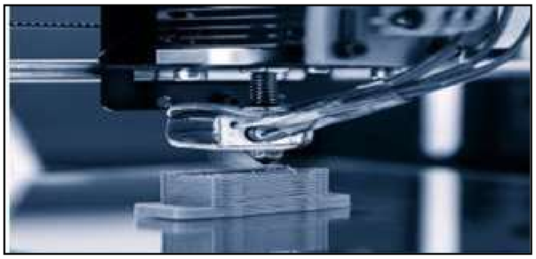

Fig. 5 Operating Machine

Neuromorphic computing may be used to enhance aspects of large-scale initiatives and product personalization. It could be used to analyse massive amounts of data from environmental sensors more quickly.

Depending on the requirements of the business, these sensors could measure water content, temperature, radiation, and other parameters. By identifying patterns in these data, the neuromorphic computing structure might make it simpler to draw useful inferences.

Due to the characteristics of the materials used to construct them, neuromorphic devices may also facilitate product modification. These substances can be turned into solutions that are simple to control. They can be processed through additive manufacturing in liquid form to produce products that are especially suited to the requirements of the user.

Artificial Intelligence

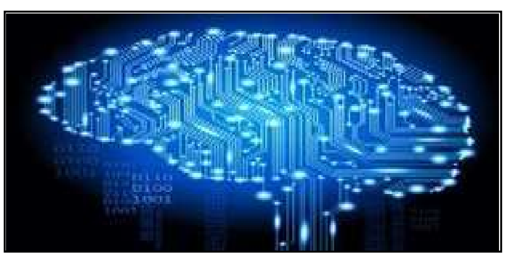

Fig. 6 Neuromorphic Brain-System

By definition, the goal of neuromorphic computing is to replicate how the human brain works.Neurons in the brain receive, analyze, and transmit signals in a very quick and energy-efficientmanners.

As a result, it makes sense that tech experts, particularly those working in the area of artificial intelligence (AI), would be fascinated by this kind of automation. As the name implies, experts in the area of AI concentrate on one specific aspect of the brain: intelligence.

The capacity of the intellect to gather and use knowledge is known as intelligence. It would be advantageous for the two fields to work together moving forward because this idea is so closely related to neuromorphic computing [3].

Imaging

Fig. 7 Camera Lens

Similar to how the human eye creates pictures, neuromorphic vision sensors do the same. This type of surveillance technology is "event-based." This demonstrates that they create images in response tolight intensity (an exterior signal) rather than an internal signal.

Furthermore, they move at a faster pace independent of conventional frame rates. In a neuromorphic sensor, each pixel functions autonomously of its neighbours. Additionally, the gadget communicateschanges to each pixel almost instantly. These processes work together to make data use much more effective.

Like their conventional counterparts, these sensors do not exhibit motion blur or a delayed reactionto the environment. Incorporating neuromorphic vision devices into virtual and augmented reality technology may be advantageous given these qualities.

Current/Latest R&D works in the field :-Intel's Loihi Chip

Fig. 8 Intel's Loihi Chip

Intel is one of many large and minor chip manufacturers creating silicon for neuromorphic computing. One of the most well-known neuromorphic computing processors is Loihi, a product of Intel, and TrueNorth, a product of IBM. Although other vendors are also trying to gain traction in a global market that Verified Research forecasts will grow from $22.06 million last year to

$3.5 billion by 2028. These like Qualcomm and Samsung to smaller firms like BrainChip and Applied Brain Research.

Intel Pohoiki Beach

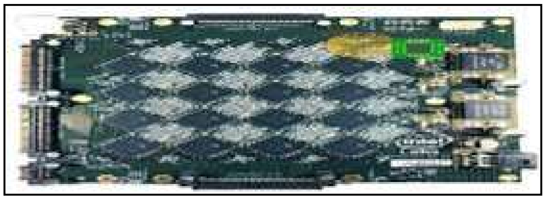

Fig.9 Intel's Pohoiki Beach Computers

The Pohoiki Beach neuromorphic system serves as an example of the advantages of a specialized architecture for new uses, including some of the computational challenges that the internet of things (IoT) and autonomous devices find challenging to support.

For a variety of real-world applications, such as autonomous vehicles, smart homes, and cybersecurity, we can anticipate realizing orders of magnitude increases in speed and efficiency by using this type ofspecialized system as opposed to general-purpose computing technologies.

Brain Scales

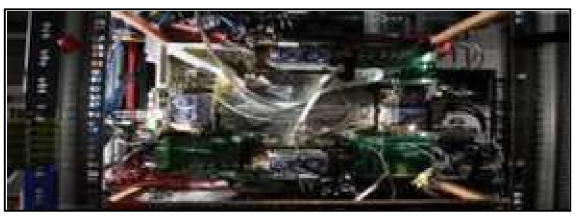

Fig. 10 BrainScales

The goal of the BrainScaleS research is to comprehend and simulate how various spatial and temporal scales interact to process information in the brain. The in-vivo biological experimentation andcomputational analysis are the core components of Brain Scale S' fundamentally novel method. Individual neurons, larger populations of neurons, and even complete functional brain regions can be considered as spatial scales.

A variety of temporal scales are important for learning and development, from milliseconds for event- based plasticity mechanisms to hours or days. To allow an artificial synthesis of cognitive abilities resembling those of the cortex, general theoretical principles will be extracted for the project. For this, we will use both numerical simulations on peta flop supercomputers and a completely different non- von Neumann hardware architecture.

In-depth information from higher cortical regions that have been carefully chosen will be combined with neurobiological data from the early perceptual visual and somatosensory systems. We'll create and use useful databases as well as brand-new, project-specific experimental tools and procedures. Inorder to comprehend the computational role of the complex multi-scale dynamics of in vivo neural systems, new theoretical concepts and methodologies will be created. Innovative in-vivo studies will be conducted to direct this critical comprehension.

The Tianjic Chip

Fig.11 The Tianjic Chip

The Tianjic Chip is the first hybrid processing chip designed after the human brain for the creation of artificial general intelligence (AGI). Local memory access and computation are integrated within each processor core of its decentralized multi-core architecture. There are 156 functional components on each chip, which together make up about 40,000 neurons and 10 million synapses.

It not only supports the application of neuromorphic computing models and machine learning methods with a focus on neuroscience but also supports their hybrid modelling. For the creation of AGI, the Tianjic chip offers a general processing platform.

Conclusion:

In conclusion, neuromorphic computing represents a revolutionary paradigm shift in computer engineering, drawing inspiration from the intricate architecture and dynamic functionality of the human brain and nervous system. Departing from traditional computing approaches, neuromorphic systems strive to emulate the parallel processing and distributed memory capabilities inherent in biological neural networks.

The imperative for embracing neuromorphic computing arises from the inherent limitations of conventional computing architectures, exemplified by the von Neumann design. With memory and computation segregated in traditional systems, the inefficiencies stemming from the von Neumann bottleneck and computation-memory gap have become increasingly pronounced. However, neuromorphic computing offers a novel solution by integrating memory and computation, leveraging artificial neurons and electric spikes to enable simultaneous processing and storage of information.

Key components of neuromorphic computing, including artificial neurons and electric spikes, embody the principles of the nervous system, facilitating enhanced efficiency, scalability, and performance. By transcending the constraints of traditional computing architectures, neuromorphic systems hold promise for revolutionizing tasks such as large-scale data processing, pattern recognition, and real-time controls.

Moreover, recent advancements in neuromorphic computing, exemplified by initiatives such as Intel's Loihi chip and BrainScaleS research, underscore the growing significance of this field. With ongoing research and development efforts aimed at harnessing the potential of neuromorphic computing, the future holds immense promise for unlocking new frontiers in artificial intelligence, medical applications, and large-scale operations.

As we continue to explore the capabilities of neuromorphic computing and its applications across various domains, collaboration across disciplines, from neuroscience to materials science, will be essential. By fostering interdisciplinary partnerships and embracing innovative approaches, we can unlock the full potential of neuromorphic computing and usher in a new era of computational prowess and intelligence.

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