EMERGING TRENDS IN COMPUTATION & ARTIFICIAL INTELLIGENCE

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Emerging Trends in Computation & Artificial Intelligence

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CHAPTER - 16
EMBODIED NEUROMORPHIC INTELLIGENCE

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ABSTRACT

Neuromorphic computing, also known as neuromorphic engineering, is an approach to computing that mimics the way the human brain works. It entails designing hardware and software that simulate the neural and synaptic structures and functions of the brain to process information. Neuromorphic computing is a novel computing method inspired by human brain computation and thus is also called brain-inspired computing. Neuromorphic computing architectures enable in-memory analog computing technology; hence, memory and processor are not physically separated. This type of computation technology can address the drawbacks of the von Neumann architecture.

Today, as artificial intelligence (AI) systems scale, they'll need state-of-the-art hardware and software behind them. Neuromorphic computing can act as a growth accelerator for AI, boost high-performance computing and serve as one of the building blocks of artificial superintelligence. Experiments are even underway to combine neuromorphic computing with quantum computing.[2]Neuromorphic computing has been cited by management consulting company Gartner as a top emerging technology for businesses.[3] Similarly, professional services firm PwC notes that neuromorphic computing is an essential technology for organizations to explore since it's progressing quickly but not yet mature enough to go mainstream.

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1.Neuromorphic Computing

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2. Benefits of Neuromorphic Computing

Neuromorphic computing offers a wide range of benefits, positioning it to be a transformative addition to the world of advanced computing.

Faster Than Traditional Computing

Neuromorphic systems are designed to imitate the electrical properties of real neurons more closely, which could speed up computation and use less energy. And because they operate in an event-driven way, where neurons only process information when relevant events occur, they can generate responses "pretty much instantly," Alexander Harrowell, a principal analyst at tech consultancy Omdia, told Built In.

Low latency is always beneficial, but it can make a big difference in tech that relies on real-time sensor data processing, like IoT devices.

Excellent at Pattern Recognition

Because neuromorphic computers process information in such a massively parallel way, they are particularly good at recognizing patterns. By extension, this means they're also good at detecting anomalies, Accenture Labs' Danielescu said, which can be useful in anything from cybersecurity to health monitoring.

Able to Learn Quickly

Neuromorphic computers are also designed to learn in real time and adapt to changing stimuli, just as humans can, by modifying the strength of the connections between neurons in response to experiences.

“Neural networks are made to constantly adjust,” Bron said. “They’re made to constantly progress and change, which allows it to get better and better.”

This versatility can be valuable in applications that require continuous learning and quick decision-making, whether that’s teaching a robot to function on an assembly line or having cars navigate a busy city street autonomously.

Energy Efficient

One of the most prominent advantages of neuromorphic computing is its energy efficiency, which could be especially beneficial in the making of artificial intelligence — a notoriously energy-intensive industry.

Neuromorphic computers can process and store data together on each individual neuron, as opposed to having separate areas for each the way von Neumann architectures do. This parallel processing allows multiple tasks to be performed simultaneously, which can lead to faster task completion and lower energy consumption. And spiking neural networks only compute in response to spikes, meaning only a small portion of a system’s neurons use power at any given time while the rest remain idle.

3.Neuromorphic Computing Uses

Despite these challenges, neuromorphic computing is still a highly funded field and is projected to exceed $20 billion by 2030. And experts are enthusiastic about its potential to revolutionize various tech fields, thanks to its unique ability to mimic the brain’s information processing and learning capabilities.

Self-Driving Cars

Self-driving cars must make instant decisions to properly navigate and avoid collisions, which can require extensive computing power. By employing neuromorphic hardware and software, self-driving cars could be able to carry out tasks faster than if they used traditional computing, all with lower energy consumption. This can make for quicker response times and corrections on the road while also keeping overall energy emissions down.

Drones

Using neuromorphic computing, drones could be just as responsive and reactive to aerial stimuli as living creatures. This technology may allow vision-based drones to autonomously traverse complex terrain or evade obstacles. A neuromorphic-engineered drone can also be programmed to only increase its energy usage when processing environmental changes, allowing it to rapidly respond to sudden crises during rescue or military operations.

Edge AI

Neuromorphic computing’s energy efficiency, adaptability and ability to process data in real time make it well-suited for edge AI, where computations are done locally on a machine (like a smart device or autonomous vehicle) rather than in a centralized cloud computing facility or offsite data center, requiring the real-time processing of data from things like sensors and cameras.

With its event-driven and parallel-processing capabilities, neuromorphic computing can enable quick, low-latency decision-making. And its energy efficiency can extend the battery life of these devices, reducing the need to recharge or replace edge devices around the home. In fact, Bron said some studies have found neuromorphic computing to be 100 times more effective in terms of battery efficiency than normal computing.

Robotics

Neuromorphic systems can enhance the sensory perception and decision-making capabilities of robots, enabling them to better navigate complex environments (like a factory floor), recognize objects and interact with humans more naturally.

Fraud Detection

Neuromorphic computing excels at recognizing complex patterns, enabling it to identify subtle signs of fraudulent activity or security breaches, such as unusual spending behavior or counterfeit login attempts. Plus, the low latency processing of neuromorphic computing could enable a swifter response once the fraud has been detected, such as freezing accounts or alerting the proper authorities in real time.

Neuroscience Research

Through its use of brain-inspired neural networks, neuromorphic computing hardware is used to advance our understanding of human cognition. As researchers try to recreate our thought processes in electronics, they may learn more about the brain's inner workings.

The Human Brain Project, an EU-funded group made up of some 140 universities, teaching hospitals and research centers, spent ten years attempting to create a human brain using two neuromorphic supercomputers. It concluded its work in September of 2023.

Researchers have also created a national hub for neuromorphic computing in the United States. By providing wider access to neuromorphic computing technology, researchers hope to spearhead more research initiatives in neuroscience, AI and STEM disciplines.

4.Neuromorphic Devices

While neuromorphic computing is still in the early stages, a few neuromorphic devices have been invented. Here are a few examples:

- **IBM's NorthPole:** IBM's NorthPole chip is energy-efficient while being 4,000 times faster than its predecessor TrueNorth — IBM's first neuromorphic chip with 1 million neurons and 256 million synapses.

- **Intel's Loihi 2:** Loihi 2 is Intel's second-generation neuromorphic chip that displays greater energy efficiency and 15 times more resource density than the first-generation chip, supporting a broader range of neuro-based algorithms.

- **SpiNNaker:** Developed at the University of Manchester, a SpiNNaker machine is a parallel computing platform that can simulate one billion simple neurons, making it a key tool for neuroscience research.

- **NeuRRAM:** Created by a team of researchers based in the U.S. and China, NeuRRAM is an AI inference chip that is designed to operate with just a "fraction of energy" used by traditional AI chips, supporting AI in edge devices.

In addition, a team of researchers developed a neuromorphic device called a spin-memristor, which could reduce AI's energy consumption to one-hundredth of what it currently uses. Scientists at Los Alamos National Library followed this up with the creation of memristors, which can remember previous electrical signals and power the artificial synapses that are the foundation of neuromorphic computers. And researchers in Germany are building neuromorphic computers with the help of microLED technology.

Neuromorphic computing remains limited in scope, but these advancements promise to make the technology more widely available in the not-so-distant future.

Requirements of Intelligent Robots

Recent developments in machine learning, supported by increasingly powerful and accessible computational resources, led to impressive results in robotics-specific applications[2,3,4]. Nevertheless, except for the case of precisely calibrated robots performing repetitive operations in controlled environments, autonomous operations in natural settings are still challenging due to the variability and unpredictability of the dynamic environments in which they act.

The interaction with uncontrolled environments and human collaborators requires the ability to continuously infer, predict and adapt to the state of the environment, of humans, and of the robotic platform itself, as described in Box 1. Current machine learning, deep networks, and AI methods for robotics are not best suited for these types of scenarios and their use still has critical roadblocks that hinder their full exploitation. These methods typically require high computational (and power) resources: for example deep networks have a very large number of parameters, they need to be trained with very large datasets, and require a large amount of training time, even when using large Graphics Processing Unit (GPU) clusters.

5. Neuromorphic perception

Robots typically include many sensors that gather information about the external world, such as cameras, microphones, pressure sensors (for touch), lidars, time-of-flight sensors, temperature sensors, force-torque sensors or proximity sensors. In conventional setups, all sensors measure their corresponding physical signal and sample it at fixed temporal intervals, irrespective of the state and dynamics of the signal itself. They typically provide a series of static snapshots of the external world. When the signal is static, they keep on transmitting redundant data, but with no additional information, and can miss important samples when the signal changes rapidly, with a trade-off between sampling rate (for capturing dynamic signals) and data load. Conversely, in most neuromorphic sensory systems, the sensed signal is sampled and converted into digital pulses (or “events”, or “spikes”) only when there is a large enough change in the signal itself, using event-based time encoding schemes[15,16] such as pulse-density or sigma-delta modulation[17]. The data acquisition is hence adapted to the signal dynamics, with the event rate increasing for rapidly changing stimuli and decreasing for slowly changing ones. This type of encoding does not lose information[18,19,20] and is extremely effective in scenarios with sparse activity. This event-representation is key for efficient, fast, robust and highly-informative sensing. The technological improvement comprises a reduced need for data transmission, storage and processing, coupled with high temporal resolution – when needed – and low latency. This is extremely useful for real time robotic applications.

Starting from the design of motion sensors and transient imagers[21], the first event-driven vision sensors with enough resolution, low noise and sensor mismatch – the Dynamic Vision Sensor (DVS)[22] and Asynchronous Temporal Imaging Sensor (ATIS)[23] – triggered the development of diverse algorithms for event-driven visual processing and their integration on robotic platforms[24]. These sensor information encoding methods break decades of static frame encoding as used by conventional cameras. Their novelty calls for the development of a new principled approach to event-driven perception. The event-driven implementation of machine vision approaches vastly outperforms conventional algorithmic solutions in specific tasks such as fast object tracking[25], optical flow[26,27,28] or stereo[29] and Simultaneous Localisation and Mapping (SLAM)[30]. However, these algorithms and their hardware implementations still suffer from task specificity and limited adaptability.

The problem of tactile perception is further complicated by three factors. First, by the sheer number of available different physical transducers. Second, by the difficulty in interfacing the transducers to silicon readout devices. This is unlike the situation in vision, where silicon photo-diodes can capture light and are physically part of the readout device. Third, there are the engineering challenges in integrating tactile sensors on robotic platforms, comprising miniaturization, and design and implementation on flexible and durable materials with good mechanical properties, wiring, and robustness. Very few native neuromorphic tactile sensors have been developed so far[45,46,47,48] and none has been stably integrated as part of a robotic platform, besides lab prototypes. While waiting for these sensors to be integrated on robots, existing integrated clock-based sensing can be used to support the development of event-driven robotics applications. In this “soft” neuromorphic approach, the front end clocked samples are converted to event-based representation by means of algorithms implemented in software[49,50,51] or embedded on Digital Signal Processors (DSPs)[52] or FPGAs[53,54].

The same approach is valuable also in other sensory modalities, such as proprioception55,56, to support the development of event-driven algorithms and validate their use in robotic applications. However, it is not optimal in terms of size, power, and latency.

For all sensory modalities, the underlying neuromorphic principle is that of "change detection", a high level abstraction that captures the essence of biological sensory encoding. It is also a well defined operation that allows algorithms and methods to extract information from data streams15 to be formalised. Better understanding the sophisticated neural encoding of the properties of the sensed signal and their relation to behavioural decisions of the subject57 – and their implementation in the design of novel neuromorphic sensors – would enhance the capability of artificial agents to extract relevant information and take appropriate decisions.

State-dependent intelligent processing

State-dependent intelligent processing is a computational framework that can support the development of more complex neuromorphic intelligent systems. In biology, real neural networks perform state-dependent computations using WTA-type working memory structures maintained by recurrent excitation and modulated by feedback nhibition121,122,123,124,125,126. Specifically, modelling studies of state-dependent processing in cortical networks have shown how coupled WTA networks can reproduce the computational properties of Finite State Machines (FSMs)101,123,127. An FSM is an abstract computing machine that can be in only one of its n possible states, and that can transition between states upon receiving an appropriate external input. True FSMs can be robustly implemented in digital computers that can rely on bit-precise encoding. However, their corresponding neural implementations built using neuromorphic SNN architectures, are affected by noise and variability, very much like their biological counterparts. In addition to exploiting the stabilising properties of WTA networks, the solution that neuromorphic engineers found to implement robust and reliable FSM state-dependent processing with noisy silicon neuron circuits is to resort to dis-inhibition mechanisms analogous to the ones found in many brain areas128,129. These hardware state-dependent processing SNNs have been denoted as Neural State Machines (NSMs)101,105. They represent a primitive structure for implementing state-dependent and context-dependent computation in spiking neural networks. Multiple NSMs can interact with each other in a modular way and can be used as building blocks to construct complex cognitive computations in neuromorphic agents105,130.

Neuromorphic sensors, computational substrates and actuators are combined to build autonomous agents endowed with embodied intelligence, by means of brain-like asynchronous, digital communication. Existing agents range from monolithic implementations - whereby sensor is directly connected to a neuromorphic computing device - to modular implementations, where distributed sensors and processing devices are connected by means of a middleware abstraction layer, trading off compactness and task-specific implementations with flexibility. Both approaches would benefit from the standardisation of the communication protocol

REFERENCES

[1]. https://www.sciencedirect.com/topics/materials-science/neuromorphic-computing

[2]. https://builtin.com/artificial-intelligence/neuromorphic-computing

[3]. https://direct.mit.edu/neco/article/34/6/1289/110645/Advancements-in-Algorithms-and-

[4]. Neuromorphic

[5]. 4.LeCun, Y., Bengio, Y. & Hinton, G. Deep learning. Nature **521**, 436–444 (2015). Schmidhuber, J. Deep learning in neural networks: an overview. Neural Netw. **61**, 85–117 (2015).