New (Neuromorphic) Computing

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1. Introduction

I spent most of my career working on computers using various software, some of which I developed myself. However, I really don't consider myself a computer (or software) professional, as I've always remained focused on the application or end product, not the computing system or language that helps me achieve it.

In fact I tend to be very dismissive of phrases like smart grid (grids, including their computer systems are REALLY dumb), and artificial intelligence (AI, artificial, yes, intelligent, not so much).

Yes I understand some of the devices that use AI have achieved useful results, but with several major drawbacks.

Finally, a relatively new class of AI described in the title may achieve a degree of intelligence, and in any case is a major advance in computing. Why? Look at its name, it imitates the human brain.

2. AI

Today's workhorse AI software relies on a deep learning algorithm known as a backpropagation neural network (BPNN), which enables AI systems to learn from their mistakes as they are trained. In a preprint posted on arXiv in August, Andrew Sornborger, a physicist at Los Alamos, and colleagues reported programming the first-generation Loihi to carry out backpropagation. The chip learned to interpret a commonly used visual data set of handwritten numerals as quickly as conventional BPNNs, while drawing just 1/100 as much power. [1]

Author's Comment: Loihi is Intel's neuromorphic chip. See section 3 for more information.

Untrained neural network models are like new-born babies: They are created ignorant of the world, and it is only through exposure to the world, experiencing it, that their ignorance is slowly relieved. Algorithms experience the world through data. So by training a neural network on a relevant dataset, we seek to decrease its ignorance. The way we measure progress is by monitoring the error produced by the network each time it makes a prediction. The way we achieve progress is by minimizing that error gradually in small steps. The errors are portals to discovery. [2]

In unpublished work, Wolfgang Maass, a computer scientist at the Graz University of Technology, and his colleagues have developed a neuromorphic system that carries out BPNN learning with 1/1000 as much power as standard graphic processing unit (GPU)-driven AI. [1]

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[1] Robert F. Service, Science, "Learning curve," Oct 1, 2021, https://www.science.org/content/article/new-brain-inspired-chips-could-soon-help-power-autonomous-robots-and-self-driving-cars

[2] Chris Nicholson, Pathmind, "A Beginner's Guide to Backpropagation in Neural Networks," https://wiki.pathmind.com/backpropagation

"It's not clear what the killer app will be for neuromorphic computing," Maass says, but he thinks robotic devices that need to consume minimal power to sense their surroundings and navigate through them are a likely prospect.

3. How Your (& a Neuromorphic) Brain Works

In place of standard computing architecture, which processes information linearly, neuromorphic chips emulate the way our brains process information, with myriad digital neurons working in parallel to send electrical impulses, or spikes, to networks of other neurons. Each silicon neuron fires when it receives enough spikes, passing along its excitation to other neurons, and the system learns by reinforcing connections that fire regularly while paring away those that don't. The approach excels at spotting patterns in large amounts of noisy data, which can speed learning. Because information processing takes place throughout the network of neurons, neuromorphic chips also require far less shuttling of data between memory and processing circuits, boosting speed and energy efficiency.[1]

This week, Intel released the second generation of its neuromorphic chip, Loihi. It packs in 1 million artificial neurons, six times more than its predecessor, which connect to one another through 120 million synapses. Other companies, such as BrainChip and SynSense, have also recently rolled out new neuromorphic hardware, with chips that speed tasks such as computer vision and audio processing. Neuromorphic computing "is going to be a rock star," says Thomas Cleland, a neurobiologist at Cornell University. "It won't do everything better. But it will completely own a fraction of the field of computing."

4. Energy Applications

Since this paper is being written for Energy Central, I will identify some potential applications for neuromorphic computing in the following subsections.

4.1. Smelling

Sensing unique smells is tough for small computers. Sure, you can take a sample of the air, take it to a mass spectrometer and it will tell you the exact composition, but utility workers rarely carry these around in their trucks (they are huge and delicate). There are also other analytical instruments that can identify specific chemicals in the air under most circumstances. However by using neuromorphic techniques, …*researchers from Intel Labs and Cornell University demonstrated the ability of Intel's neuromorphic research chip, Loihi, to learn and recognize hazardous chemicals in the presence of significant noise and occlusion. Loihi learned each odor with just a single sample, without disrupting its memory of previously learned scents. It demonstrated superior recognition accuracy compared with conventional state-of-the-art methods, including a deep learning solution that required 3,000 times more training samples per class to reach the same level of classification accuracy.*[3]

What chemicals might it be useful for an energy utility to smell? How about natural gas (methane) or other hazardous compounds leaking, or ozone from arcing electrical apparatus.

[3] Intel, "Computers That Smell: Intel's Neuromorphic Chip Can Sniff Out Hazardous Chemicals," https://newsroom.intel.com/news/computers-smell-intels-neuromorphic-chip-sniff-hazardous-chemicals/#gs.csc29w

4.2. Seeing

Neuromorphic vision sensors are bio-inspired cameras that capture the vitality of a scene, mitigating data redundancy and latency. Event-based, these sensors bring autonomy closer to reality and find utility in high-speed, vision-based applications in areas such as industrial automation, consumer electronics and autonomous vehicles.[4]

“Why do we say that an event-based vision sensor is neuromorphic? Because each pixel is a neuron, and it totally makes sense to have the artificial intelligence next to the pixel,” Pierre Cambou, principal analyst at Yole Développement (Lyon, France) told EE Times.

Neuromorphic sensing originates from the development of a “silicon retina” by Misha Mahowald at the Institute of Neuroinformatics and ETH Zurich in 1991. Mimicking the human retina, Mahowald explained, “this silicon retina reduces the bandwidth by subtracting average intensity levels from the image and reporting only spatial and temporal changes.” This inspiration drives the concept behind the Dynamic Vision Sensor (DVS) and has led to the creation of a myriad of startups in recent years. The Swiss firm iniVation is among them.

… Its neuromorphic DVS chip, dubbed DAVIS346, emulates the properties of the human retina. Only local pixel-level changes are transmitted as they occur, resulting in a stream of events at microsecond time resolution, equivalent to conventional vision sensors—but with far less data. Power (up to 90 percent less), data storage and computational requirements are significantly reduced, while sensor dynamic range (above 120 dB) is increased thanks to local processing, the company claimed.

With a network of 300 customers, iniVation has collaborated on IBM’s TrueNorth brain-inspired chip with researchers at the University of Pennsylvania, University of Zurich and the U.S. Defense Advanced Research Projects Agency. That research focused on autonomous drone flights. A European Union initiative focused on a smart sustainable city project.

“…Autonomous drone flights.” What could an electric utility do with autonomous drones with really good, really fast vision? How about surveying all of its T&D grid looking for impending (or current) problems, or immediately responding to outages.

5. Size (and Power Consumption) Matters

One of the best things about neuromorphic computing elements: they are very small, and don’t use much power. Intel, using it Loihi chip created a range of neuromorphic computer arrays. These range from the largest:

Today, Intel announced the readiness of Pohoiki Springs, its latest and most powerful neuromorphic research system providing the computational capacity of 100 million neurons. The cloud-based system will be made available to members of the Intel Neuromorphic Research Community (INRC), extending their neuromorphic work to solve larger, more complex problems.[5]

[4] Anne-Françoise Pelé, EE/Times, “Neuromorphic Vision Sensors Eye the Future of Autonomy,” April 21, 2020, https://www.eetimes.com/neuromorphic-vision-sensors-eye-the-future-of-autonomy/

[5] Intel, “Intel Scales Neuromorphic Research System to 100 Million Neurons,” March 18, 2020, https://newsroom.intel.com/news/intel-scales-neuromorphic-research-system-100-million-neurons/#gs.csvcbr

"Pohoiki Springs scales up our Loihi neuromorphic research chip by more than 750 times, while operating at a power level of under 500 watts. The system enables our research partners to explore ways to accelerate workloads that run slowly today on conventional architectures, including high-performance computing (HPC) systems."

To the smallest version of this family, which would probably be adequate for many applications:

Similarly, Intel's smallest neuromorphic system, Kapoho Bay, comprises two Loihi chips with 262,000 neurons and supports a variety of real-time edge workloads. Intel and INRC researchers have demonstrated the ability for Loihi to recognize gestures in real time, read braille using novel artificial skin, orient direction using learned visual landmarks and learn new odor patterns – all while consuming tens of milliwatts of power. These small-scale examples have so far shown excellent scalability, with larger problems running faster and more efficiently on Loihi compared with conventional solutions. This mirrors the scalability of brains found in nature, from insects to human brains.