An Analysis of Neuromorphic Computing in Modern Technology

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Abstract: ***According to IT experts, neuromorphic computing may play a key role in bringing about the fourth AI revolution. Throughout time, as the hardware industry has expanded, we have seen neuromorphic chips take control. It will improve other chips' hardware platforms so that each can handle the unique AI workloads for which it was intended. Several experts think neuromorphic computing has the potential to alter the strength, effectiveness, and capacities of algorithms in artificial intelligence while also revealing new information about cognition. Energy economy, execution speed, resilience against local failures, and learnability are key advantages of neuromorphic computing over conventional methods. Neuromorphic computing may be a game-changer for space applications where mission success depends on rapid and autonomous processing of a wide range of incoming information from various sources. It was shown that the SIF model had a 91.5% accuracy rate and had reduced the number of steps by adopting an early exit strategy in order to explore design space. The RIF model was only able to achieve less than 85% accuracy, no matter the number of steps taken. For design space exploration, there are design and control time knobs that, while lowering inference latency, provide accuracy that is comparable to or slightly below that of full precision models. In edge artificial intelligence, Spiking neural networks (SNNs), motivated by biological neurons, have been investigated as a possible neuromorphic computing solution for the incorporation of AI algorithms in edge devices due to their low energy consumption, in order to meet this difficulty. Due to the LFNL approach's use of spike activation, which requires a limited number of training time steps (T) to optimize, classification accuracy is slightly lower than that of traditional federated learning-based ANNs. This review article examines the use of neuromorphic computing in three domains: unattended ground sensors, space, and wireless edge artificial intelligence.***

Keywords: Ground Sensors, Space, Wireless Edge Artificial Intelligence, Neural Networks, Neuromorphic Computing

1. Introduction

Hardware structures known as neuromorphic computers imitate the computational phenomenology of the brain. This contrasts with neural network accelerators, which aim to speed up the basic computation and data flows of neural network models used in machine learning. Examples of these accelerators are the Google TPU and the Intel Neural Compute Stick. In order to establish a spiking communication architecture for computing, neuromorphic computers mimic the integrate and fire neuron dynamics of the brain. Although neural networks are inspired by the brain, they greatly oversimplify how the brain computes. In terms of the real computing model of the brain, neuromorphic architectures are more accurate (albeit, still simplified). Over traditional CPU designs, neuromorphic computing models predict a 1000x power increase.

An ordinary contemporary desktop Processor runs at 65W with a clock speed of 2-3 GHz. The calculation shows that a typical CPU operation should cost on the order of nano-joules of energy if we assume that a handful (a number less than 10) of clock cycles are required on average for a single operation. A NMC, on the other hand, relies on synaptic events for its fundamental function, and the typical NMC system used today costs on the order of pico-joules of energy per synaptic event. The loose foundation for the 1000x power gain is the difference in base-operation energy cost of three orders of magnitude.

There is a reason why Neuromorphic computing has an advantage other than its sparsity and event driven nature are as follows.

First, there are more advanced communication protocols between components of massively parallel basic computing that share memory. The other is that a spike is seen as a single bit of information being transmitted by digital NMC systems. One of the intriguing aspects of NMC designs is this temporal dynamic. SNNs can effectively extract temporal information from time-dependent data since time is integrated into information propagation and processing. Also, the computing model's use of time is an energy-free information exchange; the precise moment a spike appears has significant significance.

First, there are more advanced communication protocols between components of massively parallel basic computing that share memory. The other is that a spike is seen as a single bit of information being transmitted by digital NMC systems. As these methods only convey the value of an 1, sending the value of a 0 requires no energy; it is merely the lack of a spike. One of the intriguing aspects of NMC designs is this temporal dynamic. SNNs can effectively extract temporal information from time-dependent data since time is integrated into information propagation and processing. Also, the computing model's use of time is an energy-free information exchange; the precise moment a spike appears has significant significance.

Wireless Edge Artificial Intelligence

Machine intelligence, or artificial intelligence created by humans as a replacement for the usage of human brains, is known as artificial intelligence. It is implemented as an artifact and is capable of performing any tasks that people can perform as well as those that humans are incapable of performing. To assist those who speak different languages, it is employed in the airport's natural language generating system. It is utilized in voice recognition by Google AI or Alexa. Since the Internet of Things (IoT) and mobile computing have developed so quickly, billions of linked devices, including robots, actuators, sensors, and autonomous cars, have produced enormous volumes of data. This tendency has led to the development of an effective method called edge artificial intelligence (AI), which combines edge computing with AI, to allow devices at the edge of a network to locally process and analyze data without sending it to a centralized server. In addition to facilitating the protection of data privacy, such a feature significantly lowers data traffic and network latency. Deep learning of neural networks trained for voice recognition, picture and video categorization, and object identification in edge AI has also led to previously unheard-of accuracy levels.

Edge AI still has to overcome the two following major obstacles in spite of these advantages. First off, advanced learning techniques and, more critically, sufficiently large training datasets are prerequisites for current AI-based systems. As a result, it is virtually hard to train useful AI models due to the small amounts of local datasets that are readily available to edge devices. Second, energy-constrained edge devices are unable to locally train or analyze data due to machine learning algorithms' typical computational and energy demands.

Without sending raw data to a server, FL allows several collaborating devices to locally train a machine learning model (i. e., each with its own data, in parallel). The devices in this situation merely upload parameters (or gradients) to a centralized server for global model aggregation. The procedure is then continued until convergence with the new model parameters delivered back to the devices for the subsequent training session. FL not only enables edge AI to produce models with a similar level of quality to centralized learning, but it also lowers data traffic and aids in data privacy protection. For these reasons, FL has lately been used in medical applications that need privacy protection, such as medical picture categorization.
Given the central coordinator in FL, all clients and devices must have confidence in the central server, and the variety of edge devices limits the training pace. Decentralised FL, where model parameters are communicated exclusively among networked devices without utilizing a central server, has been proposed as a solution to this problem. Nevertheless, higher training delay is the result of periodically cycling model aggregation among devices. Even though it does provide a solution for privacy-enhancing and reliable model training under insufficient datasets at edge devices, deep learning-based model training can consume a significant amount of energy, further preventing the application of decentralized FL in energy-constrained edge devices. Spiking neural networks (SNNs), which are motivated by biological neurons, have been proposed and investigated as a possible neuromorphic computing solution for the incorporation of AI algorithms in edge devices due to their low energy consumption, in order to meet this difficulty. SNNs use Integrate-and-Fire (IF) or Leaky IF (LIF) neuron units to work with continuous spatiotemporal dynamics and discrete spike occurrences, simulating the electrical activity of human-brain systems. Binary spike-based sparse computing has intrinsic parallelism over time steps, and SNNs offer quick, sparse, and energy-efficient information processing. Additionally, various attempts to increase learning capacity, energy economy, and privacy protection by fusing SNNs with FL have been attempted, although model parameters are still aggregated by a central server.

In the event of unequal and inadequate training data on edge devices, Lead federated neuromorphic learning (LFNL) enables edge devices to cooperatively train a worldwide trustworthy model while increasing privacy without a central server. Due to its decentralized federated learning and parallel training structures, LFNL effectively replaces the centralized data sharing paradigm across edge devices without the need for a centralized server, greatly reducing data traffic, enhancing data privacy, and shortening training latency when compared to current centralized learning techniques. Additionally, our suggested LFNL can significantly reduce energy usage by implementing spike-based processing capabilities, making it particularly ideal for energy-constrained edge devices. The benefits of LFNL have been empirically proved in a number of benchmark comparisons on tasks including the identification of audio, visual, and radar signals with unequal dataset distributions. Research has demonstrated that LFNL greatly outperforms the locally trained technique and provides a comparable recognition accuracy to centralized learning without generating a lot of data traffic, achieving an inference accuracy of more than 94% for each challenge. The approach yields somewhat poorer classification accuracy than that of the conventional federated learning-based ANNs because of the spike activation driven nature of LFNL, which necessitates a finite amount of training time steps (T) to optimize LFNL-SNN. For energy-constrained devices, it can, nevertheless, drastically lower energy usage. On bigger and higher-dimensional datasets (CIFAR10 and CIFAR100 datasets), a greater classification accuracy is still obtained thanks to LFNL's scalability in comparison to the current federated learning architecture. It has been demonstrated that LFNL greatly outperforms the locally trained technique and provides a comparable recognition accuracy to centralised learning without generating a lot of data traffic, achieving an inference accuracy of more than 94% for each challenge.

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Space

In order to perform an algorithmic design space exploration without neuromorphic processor specific constraints and compare Reset-Integrate-and-Fire (RIF) and Subtractive-Integrate-and-Fire (SIF) neuron types for debugging, simple control knobs in design time as well as in runtime that can be used to reduce inference latency without compromising accuracy or involving complicated and computationally expensive (SIF). SIF neurons eliminate the discontinuity in the neuron function at the time when a neuron fires, hence reducing the accuracy deterioration of converted SNNs. This is accomplished, nevertheless, at the expense of increased spiking activity.

The SIF model, which has a shorter latency and more accuracy than the RIF model, requires fewer calculations overall (RIFs consume around 84% of the SIF's operations). Thus, one can investigate the SIF model. The neural threshold of each network layer is an extra hyperparameter that may be modified for run-time control. By lowering it, one may speed up inference, albeit at the expense of a modest accuracy compromise brought on by coarser approximations of network dynamics. When training is complete, a popular approach called threshold balancing runs the full dataset through the network to normalize the neuron thresholds to the maximum ANN activity.

Nevertheless, employing the highest level of ANN activation leads to a significantly larger delay since a higher threshold causes fewer neurons to fire. Here, rather than merely selecting the highest possible activation value, we investigated threshold balancing using various activation histogram percentiles.

It has been found that as one selects lower percentiles, network latency decreases, but accuracy suffers as a result. So, we selected a percentile value where the accuracy deterioration is at its lowest. Investigating an Early Exit inference technique to reduce redundant computations and improve latency results in simpler examples being categorized earlier, resulting in fewer redundant computations and a lower average inference latency. The last layer is given a certain threshold value, and if the highest membrane potential of the neurons in the final layer crosses that value, the SNN inference is said to be finished. As a result, an efficient and dynamic SNN inference method is produced.

Here are some more specifics on how networks can be trained: According to earlier research, ANNs were trained with the restrictions of no bias and batch normalization layers. In the absence of batch-normalization, dropout layers were added after each ReLU layer to provide some degree of regularization. Instead of turning the inputs into Poisson spike trains, one can simply apply the inputs as a current to the SNN. By substituting IF spiking neuron nodes for ReLUs, the trained ANN is transformed into an iso architecture SNN. Weights were quantized to an accuracy of 8 bits. By selecting a random subset from the training set and calculating the maximum ANN activity, the SNN weights are normalized. Using BindsNET, a Python tool built on PyTorch, the SNN is implemented. Investigating an Early Exit inference technique to reduce redundant computations and improve latency results in simpler examples being categorized earlier, resulting in fewer redundant computations and a lower average inference latency. The last layer is given a certain threshold value, and if the highest membrane potential of the neurons in the final layer crosses that value, the SNN inference is said to be finished. As a result, an efficient and dynamic SNN inference method is produced. In comparison, regardless of the quantity of timesteps employed, the RIF model only managed to reach less than 85% accuracy. We altered our model to use the 98.7 percentile element from the activation histogram for threshold balancing in order to obtain quicker latency, and we ran it for only 290 timesteps to achieve an accuracy of 85%. Also, while using our Early Exit approach, the average inference timestep value is 106, which is considerably less than the situation without early exit's value of 290.

Neuromorphic computing may be a game-changer for space applications where mission success depends on rapid and autonomous processing of a wide range of incoming information from various sources.

Ground Sensors

The inherent low power characteristics of NMC, sparse connection, and event-driven processing and communication are driven by two brain-inspired concepts. In an electrical soup of 86 billion neurons, each neuron in the brain is connected to an average of 7, 000 other neurons. Also, throughout a task, not the entire brain spikes continuously. Power consumption is drastically decreased by not powering any computing parts that are not needed at any given moment.

Moreover, event-driven computation and firing dynamics characterize neurons. A neuron won't use energy to analyze a spike if it doesn't get one.

NMCs are fundamentally spatial-temporal systems that offer many modes of data processing and display. Future computing will be enabled by neuromorphic computers, which will soon be more accessible to embedded devices. The Intelligence Science for Proliferation Investment Area (IA) of the National Securities Program (NSP) should be ready for this future right away.

Applications for space-based remote sensing (RS) are deeply woven into many parts of SNL's mission domains. In three dimensions, hyper-spectrally (sensing more spectral bands), hypertemporally (higher sample rates), and hyper-spatially, remote sensing systems are rapidly developing (increasing number of smaller pixels). Due to this progression, it has become difficult to implement costly and computationally sophisticated algorithms in SWaP-restricted settings. The issue domain of remote sensing activities is collectively covered by the three broad application areas of signal processing, signal categorization, and signal interpretation.

There are many similarities between space-based RS and terrestrial RS, especially unattended ground sensors (UGS). Both mission domains need complex processing of sensor data, operate in SWaP settings with severe constraints, and get increasingly processor-intensive with each subsequent mission.

The demise of Moore's law is having an impact on cutting-edge processing application areas including supercomputers and data centers, while low-power The market for embedded sensors still has time to benefit from future performance improvements. This is due to the fact that transistor scaling has advanced more rapidly than embedded processing ICs utilized in low-power applications. However, the lamentation of the HPC and data center industries is a wakeup call to the embedded computing industry and a look into our unavoidable future.

New computer paradigms and processing platforms require years of study, development, testing, characterization, and trust-building before they can be used. Heterogeneous specialization is the way of the future of embedded systems as well as computers. The paradigm change NMC hopes to allow is fundamentally well suited for embedded computing. In contrast to the embedded world, which has flourished in its quest of the least solution, HPC has prospered in its goal of enabling maximum calculations (marching towards exascale). Therefore, rather than doing so out of necessity, we view the chance to embrace this paradigm change as a strategic benefit.

Many of the typical ANN-based ML techniques may be useful for our UGS sensing application needs, but their applicability is constrained by the power needed to apply them. It is possible to convert conventional ANN algorithms to SNN algorithms that may be used in NMC systems using a programme created by SNL called Whitstone. This makes it easier for NMC research to enter the field of low-power embedded systems and makes it possible to investigate the use of additional processing power at the sensor node. Effectively, the amount of data provided for later processing or analyst interpretation may be decreased by permitting increased processing at the sensor. The study of a more feature-rich categorization of raw sensor data and a better separation of events of interest are both made possible by the node's increased processing.

There is no denying that over the past three to four years, ML has been the hot topic in NSP, ISP, and IA. It is encouraging to see several mission-relevant funding initiatives investigating the use of ANN-type algorithms to mission-relevant issues. Results, though, seem contradictory. BALDR (examination of radio isotope identification using ML algorithms), for instance, is a superb illustration of how to successfully apply ML to a problem that is pertinent to the domain. Because high-fidelity models must be degraded in order to go to the embedded processor environment, precision is lost, other efforts have not been as effective.

Where standard ANN techniques are failing, a close examination of the corresponding ground base sensor algorithms and their transformation into SNN models for implementation on NMC hardware can result in computational and power benefits. The RS domain has already done this, and the NA-22 domain is now doing it. As its first investment in neuromorphic computing research, the NSP ISP LDRD IA supported a 2-year LDRD project with the working title "Autonomous Reconfigurable Intelligence at the Edge" in FY22. This endeavor examines the use of brain-inspired computer methods to solve challenges pertinent to the ISP mission domain. With liquid state machines (LSM), this study specifically aims to use the idea of context switching in the brain to create an algorithm that can use many ML. Many of the models also consume more power than the conventional technique for accomplishing the same work since they are either too big to implement or take too long to compute.

Additionally, a lot of the one-dimensional sensor phenomenologies used in ground sensors make it challenging to accurately distinguish between event data when examining data from a single sensor.

The LSM is an SNN-based technique that uses streaming data, a typical sort of data in the UGS domain, to conduct high dimensional feature space discrimination. This kind of neural model may combine sensor data with ease while increasing the dimension of the data, which improves discrimination. It will be simple to implement on neuromorphic hardware if the data sensor categorization algorithm makes native use of spikes. This indicates that neuromorphic research is beginning to go forward in the NSP ISP IA, which is encouraging.

2. Analysis

In edge intelligence, SNNs have been advocated because of their low energy consumption for the implementation of AI algorithms in edge devices. Quick, sparse, and energy-efficient information processing is provided by SNNs.

Achieving an inference accuracy of more than 94% for each challenge, it has been shown that LFNL significantly outperforms the locally trained approach and offers a comparable recognition accuracy to centralized learning without creating a lot of data traffic. Due to the spike activation driven nature of LFNL, which requires a finite amount of training time steps (T) to optimize LFNL-SNN, the technique produces somewhat lower classification accuracy than that of the standard federated learning-based ANNs. A solution to this would be increasing the finite amount of training time steps to a threshold value which is closer to the one required by the LFNL-SNN optimization. The training of the threshold value could be done with previous datasets. This would limit the training time steps considerably while also increasing it enough to reach a value close to the optimization of LFNL-SNN.

Most neuromorphic research is still done on von Neumann hardware with standard deep learning software. As opposed to what neuromorphic computing attempts to do, this limits the study findings to traditional approaches.

There are design and control time knobs for design space exploration that give the same or slightly less accuracy as full precision models while reducing inference latency.

3. Conclusion

Several experts think neuromorphic computing has the ability to transform the strength, effectiveness, and capacities of algorithms in AI while also revealing new information about cognition. Nevertheless, neuromorphic computing is still in its infancy and faces a number of difficulties. Neuromorphic computers require less energy (GPUs) than deep learning, machine learning, neural hardware, and edge graphics processing units. Yet, they have yet to demonstrate that they are indisputably more accurate than them. Many people prefer conventional software because of the accuracy issue, expensive expenses, and complexity of the technology. Software for neuromorphic computing is still behind the hardware. The majority of neuromorphic research is still carried out using von Neumann hardware and common deep learning software. Because neuromorphic computing aims to go beyond traditional approaches, this limits the study findings to them. Non Experts cannot access neuromorphic computers. Software developers have not yet created application programming interfaces, programming models, or languages to make neuromorphic computers more usable.

Neuromorphic research lacks clear performance and common challenge criteria. It is difficult to assess the operation of neuromorphic computers and prove their use without these rules. Neuromorphic computers can only access the currently understood parts of human cognition, which are still far from complete. If cognition requires quantum computation rather than conventional processing, neuromorphic computers would be partial representations of the human brain and would need to incorporate technologies from areas like probabilistic and quantum computing. In order to explore design space, It was demonstrated that the SIF model had a 91.5% accuracy rate and had cut the number of steps by using an early exit strategy. The RIF model was only able to attain less than 85% accuracy no matter how many timesteps were utilized.

In edge intelligence, With an inference accuracy of more than 94% for each challenge, it has been shown that LFNL significantly outperforms the locally trained method and gives a recognition accuracy equivalent to centralized learning without producing a lot of data traffic. The approach results in somewhat poorer classification accuracy than that of the conventional federated learning-based ANNs due to the spike activation driven nature of LFNL, which takes a finite amount of training time steps (T) to optimize LFNL-SNN.

4. Future Directions

Yet more investigations into design space are feasible, including backpropagation over time and semi-supervised or unsupervised learning utilizing spike timing dependent plasticity (STDP) learning rules. To improve accuracy, more study must be done on models like the SIF model and on exit strategies such as early exit strategies that minimize overhead or headcount. At the moment, processing, filtering, and extracting enormous volumes of continually received data to understand events and actions constitutes real-time change detection of information (images, texts, audio signals, etc.). Although von Neumann architecture has been used to carry out these tasks, Neuromorphic computing could enable more effective on-orbit data processing and storage by lowering the number of bytes needed to save an image and/or removing the requirement to send significant amounts of data to a ground station for image processing. For distant platforms that are deployed in space, autonomous systems are essential. The International Space Station now uses autonomous docking mechanisms. According to the Global Exploration Roadmap (GER), "advances in electronics, computer architectures, and software that enable autonomous systems to interact with people are needed and can be tapped into from commercial markets to facilitate maturity of essential capabilities. " While deep learning algorithms and neuromorphic computing are presently enabling satellites to operate autonomously, neuromorphic computing may bring about additional benefits including the ability to learn in real-time. Information security and mission assurance depend on the spacecraft's cyber status being tracked and evaluated. This might be especially useful in situations where communication lines are congested. For situational awareness on the ground, intrusion detection continuously scans communications and spacecraft bus traffic for signs of an assault in progress.

A reliable defense system would be provided by embedded intelligence made possible by NC on board a spaceship. Several of the modern space systems send the processed data from imagers and other sensors to a distant operations center. The bandwidth for this data transfer is constrained, but the capacity of the sensors is growing. Moreover, in a threat environment, connectivity with the data gathering platform may be hampered (e. g., a disrupted communication link). Even in dangerous circumstances, a neuromorphic processor might provide quick processing of sensor data at the site of acquisition and offer cybersecurity, change detection, and autonomous control capabilities. Ultimately, a well-designed neuromorphic technology can overcome a basic time-energy paradox by providing both quick analysis and low energy use.

Artificial neural networks that more closely resemble real neural networks are called spiking neural networks (SNNs). As stated in Edge Artificial Intelligence, Future research must be done to combine SNNs with Federated Learning to boost learning capacity, energy efficiency, and privacy protection, albeit model parameters are still aggregated by a central server.

In edge intelligence, The LFNL approach results in somewhat poorer classification accuracy than that of the conventional federated learning-based ANNs due to the spike activation driven nature of LFNL, which takes a finite amount of training time steps (T) to optimize LFNL-SNN. An interesting research area would be the spike driven nature of LFNL which would increase the classification accuracy by increasing the number of training time steps to optimize LFNL-SNN. An intriguing topic for investigation would be the spike-driven nature of LFNL, which would improve LFNL-SNN by increasing the amount of training time steps and improving classification accuracy.

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