Powering Next-generation Industry 4.0 by a Self-learning and Low-power Neuromorphic System

Hongyu An
Department of Electrical and Computer Engineering
Michigan Technological University
Houghton, MI USA
hongyua@mtu.edu

Dong Sam Ha
Bradley Department of Electrical and Computer Engineering
Virginia Tech
Blacksburg, VA USA
ha@vt.edu

Yang (Cindy) Yi
Bradley Department of Electrical and Computer Engineering
Virginia Tech
Blacksburg, VA USA
yangyi8@vt.edu

ABSTRACT

With the continuous development of technologies, our society is approaching the next stage of industrialization. The Fourth Industrial Revolution also referred to as Industry 4.0, redefines the manufacturing system as a smart and connected machinery system with fully autonomous operation capability. Several advanced cutting-edge technologies, such as cyber-physical systems (CPS), internet of things (IoT), and artificial intelligence, are believed as the essential components to realize Industry 4.0. In this paper, we focus on a comprehensive review of how artificial intelligence benefits Industry 4.0, including potential challenges and possible solutions. A panoramic introduction of neuromorphic computing is provided, which is one of the most promising and attractive research directions in artificial intelligence. Subsequently, we introduce the vista of the neuromorphic-powered Industry 4.0 system and survey a few research activities on applications of artificial neural networks for IoT.

KEYWORDS

Neuromorphic Computing, Industry 4.0, Reservoir Computing, Fourth Industrial Revolution

1 INTRODUCTION

Three Industrial Revolutions occurred in human history. The First Industrial Revolution occurred in the 18th century accompanying the invention of a steam engine. The extensive utilization of steam engines successfully transited the production activities of human society from hand production to machine manufacturing. Next, the Second Industrial Revolution at the beginning of the 20th century further improved productivity through the massive employment of electrification and the production line. Lastly, the Third Industrial Revolution started in the late 1950s has propelled our society into the information age, which is built upon integrated circuits, digital computers, communication theory, and the internet.

Since the Third Industrial Revolution, the computer-powered machines in modern factories have enhanced the manufacturing capability to an unprecedented level using their powerful manufacturing capability with an automatic production line. However, these machines still lack one of the essential features to further free people from tedious works, which is the capability of independent, smart, and autonomous manufacturing without any human intervention. The thrust of realizing this level of autonomous manufacturing is called the Fourth Industrial Revolution, also referred to as Industry 4.0 [1]. Industry 4.0 requires a smart and autonomous manufacturing system, which is capable of performing tasks on its own and making necessary decisions independently [2]. Thereby, the machines in Industry 4.0 demand smart sensors capturing real-time data from surroundings, the next level of communication efficiency enabling machines to collaborate for sophisticated tasks. More importantly, an unprecedently smart intelligence system controls these parts and conducts a fully autonomous operation. These unique requirements can be enabled by Cyber-Physical Systems (CPS) [3], Internet of Things (IoT) [4], and the next level of artificial intelligence. Cyber-Physical Systems map the physical world into the cyber world using smart sensors. Then, machines can communicate and operate collaboratively through Internet of Things. Lastly, harmonious collaborations and autonomous manufacturing can be achieved through intelligent systems built upon cloud computing, cognitive computing, and artificial intelligence [1]. As the core of all connected manufacturing machines, a more powerful artificial intelligence system with lower power consumption and better self-learning capability is expected in Industry 4.0. However, the advanced level of intelligence does not exist for current artificial intelligence systems, which is the biggest challenge for Industry 4.0.

Despite deep learning demonstrates the remarkable capability of Artificial Neural Networks (ANN) in solving complicated cognition tasks, the computing platforms built upon von Neumann architecture (digital domain) limit the performance and efficiency of ANN [5]-[7]. On the contrary, human brains perform multiple intelligent tasks, such as pattern recognition, reasoning, control, and movement, with an extremely low power consumption of about 20 W. The next generation of artificial intelligence should aim to rebuild a brain-like neuromorphic system, which takes full advantage of human brains to overcome the challenge of Industry

This work was supported by the National Science Foundation under CCF-1750450, ECCS-1811497, and CCF-1937487.

NANOCOM '20, September 23–25, 2020, Virtual Event, USA

ACM ISBN 978-1-4503-8083-6/20/09 $15.00
https://doi.org/10.1145/3411295.3411302

4.0. Specifically, the next generation of the neuromorphic system is necessary to include the following features:

- Organ-like sensory system (for example, eyes and ears) to capture signals from the physical world and transform them into spiking signals for Cyber-Physical Systems and Internet of Things;
- Human-like learning methodology that enables a neuromorphic system in Industry 4.0 to learn from surroundings and its experiences.

These unique features can be achieved by reverse engineering of human brains with emerging technologies at all levels of the architecture, algorithm, circuit, and device.

IoT is the internetworking of physical devices embedded with sensors, actuators, and network connectivity that enable these objects to collect and exchange data. IoT devices will be able to provide innovative services and solutions in the realms of such as smart homes, smart cities, and smart factories. It is envisioned that trillions of IoT devices such as sensors, cameras, and wearables will be connected to the Internet, forming a massive IoT ecosystem [8] [9]. Further, low power wireless technologies such as Bluetooth, Wi-Fi, ZigBee, Cellular, and RFID enable IoT devices to connect with each other over wireless links and operate in a self-organizing manner [10]. Such wireless IoT devices and systems will be a key ingredient for Industry 4.0. Figure 1 shows representative applications of wireless IoT devices, possibly powered by energy harvesting.

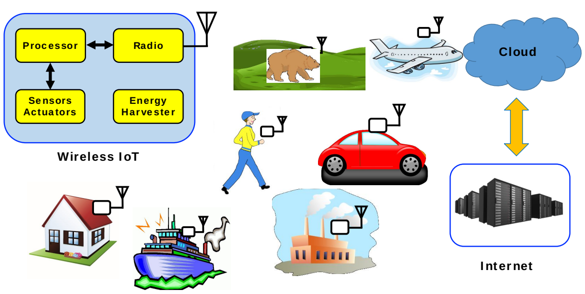

Figure 1: Representative applications of wireless IoT devices.

Practical deployment of an IoT system still faces many challenges such as data analytics, computation, transmission capabilities, connectivity, end-to-end latency, security, and privacy [10], [11]. ANNs can be used to address some of the key challenges of wired IoT devices, in which large power consumption may not be critical, while neuromorphic systems are a good choice for wireless IoT devices powered by batteries or energy harvesting.

This paper is organized as follows. Section 2 reviews earlier works on neuromorphic systems in the context of Industry 4.0 and Section 3 recent research activities on the application of ANN to IoT devices and systems. Section 4 draws the conclusions.

2 NEUROMORPHIC SYSTEM POWERED INDUSTRY 4.0

Unlike traditional manufacturing machines with isolated information processing at each machine and lack of communication with each other, the machines in Industry 4.0 should possess the capability of sensing real-world data/signals and updating them to the cloud side server for further processing and computing as shown in Figure 2 (a).

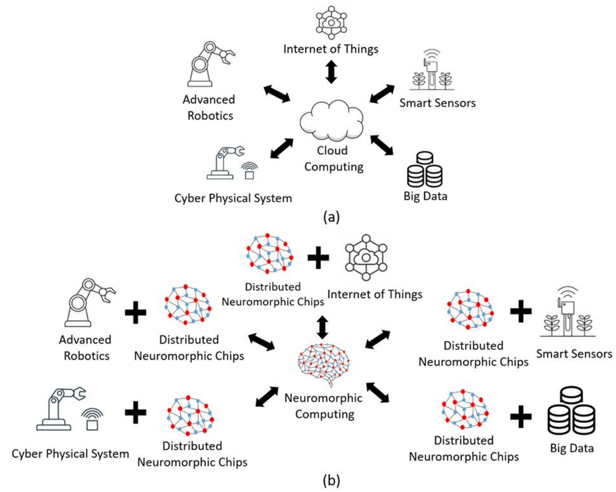

Figure 2: (a) Conventional Industry 4.0 system (b) neuromorphic-powered Industry 4.0 system.

With the assistance of powerful computational resources on the server-side, machines located across the factory can share knowledge/information, access a global library of images, map and object data centers, and accomplish the task collaboratively. However, these servers consist of conventional von Neumann-based chips with high power consumption and limited learning capability. One of the most critical drawbacks of the von Neumann architecture of digital computers is the speed and energic bottleneck of data communication between the CPU and memory [12]. Thereby, the typical computers invented in the Third Industry Revolution are able to recognize 1,000 different objects but consumes about 250 W [13]. On the contrary, a human brain performs similar cognitive and complicated tasks, such as pattern recognition, reasoning, control, and movement, with the power consumption of only about 20 W [12], [14]. The differences in the performance stem from the intrinsic difference in structures. Human brains comprise of millions of neurons connecting by trillions of synapses forming a network configuration. The latest discoveries in neuroscience indicate remarkable capabilities of human brains are attributed to three unique features: (1) neural network structure; (2) spike-based signal representation; (3) synaptic plasticity and associative memory learning [13], [15]. Firstly, the neural network structure has demonstrated its capability of handling cognition tasks in deep learning [13], [15]. Secondly, the low firing rate of spiking signals enables the brains to operate with high energy efficiency. Thirdly, neurologists prove that synaptic plasticity and associative memory learning are highly relative to the memory mechanism, which enables the brains to learn from the surroundings.

In this paper, we propose a new Industry 4.0 system built upon the brain-like neuromorphic chips illustrated in Figure 2 (b). In this system, the self-learning and low-power consumption neuromorphic chips are deployed at both the client and center sides [16]. This novel neuromorphic-powered Industry 4.0 system replaces conventional von Neumann-based chips invented in the Third Industrial Revolution with neuromorphic chips. Then each machine at the so-called light-out factory will deploy self-learning and adaptive neuromorphic chips that can seamlessly connect each other through Internet of Things.

Moreover, a network-based neuron system does not just exist in the brain, but also spreads throughout the entire human body, including the sensory and motion systems [16]. The organ-like sensory systems, such as eyes, capture the external signals, and encode them into spiking sequences in low frequency, less than thousands of Hertz [14]. The utmost low frequency of the signals in the neural system significantly reduces energy consumption. Furthermore, these organ sensors constantly receive signals from the external world enabling the system a real-time processing capability, an essential feature for creating an adaptive Industry 4.0 system. Recently, ultra-low energy and real-time neuromorphic vision system have been designed and in a commercialization track, named as iniVation Dynamic Vision Sensor [17].

The control system built upon the neural networks can make rapid and adaptive responses to the changes in the environment. For example, birds can constantly adjust the flying height and direction to avoid obstacles. The capabilities of real-time response and adaptivity of the neural network-based motion system are highly suitable for complex manufacturing tasks in Industry 4.0. The neural network-based robotics would help us to design next-generation advanced robotics for autonomous manufacturing in Industry 4.0 [16], [18-21].

2.1 Emerging Neuromorphic Architectures

Digital computers in the Third Industry Revolution are built upon the von Neumann architecture. Whereas the von Neumann architecture is designed for efficient Boolean calculations rather for neuromorphic computing. Thereby, the architecture for the next generation computers should aim to rebuild a network configuration mimicking the neural network.

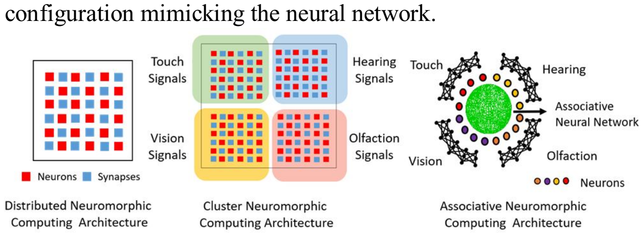

Figure 3: Emerging neuromorphic computing architectures: (1) Distributive Neuromorphic Computing Architecture (2) Cluster Neuromorphic Computing Architecture (3) Associative Neuromorphic Computing Architecture.

To address the challenge, three emerging neuromorphic architectures called Distributive Neuromorphic Computing Architecture (DNCA), Cluster Neuromorphic Computing Architecture (CNCA), and Associative Neuromorphic Computing Architecture (ANCA) are proposed in [12], [22]. Figure 3 illustrates those three emerging non-von Neumann neuromorphic architectures.

In DNCA, the neurons and synapses are distributed and placed in a network structure minimizing the distance between the computing units (neurons) and the memory units (synapses). Thereby, the computation of neural networks can be performed between adjacent neurons and synapses minimizing the energy spent on signal propagation. Compared to the digital representation, utilization of threshold neurons and the spike-based training method further reduce the power consumption. In order to realize the parallel processing feature of the brain, CNCA divides the entire network configuration of DNCA into multiple regions. Each region processes a specific signal type, such as visual and auditory signals captured by individual organ-like sensors. As a result, different signals are processed at separate neural networks in parallel. Lastly, ANCA correlates the outputs of CNCA together realizing a high-level associative memory learning capability. The associative memory learning enables the neuromorphic system to learn directly from the surroundings as well as its own experience.

2.2 Associative Memory Learning

Nowadays, constantly increasing demand for large datasets is the main bottleneck for a massive deployment of artificial neural networks. The sizes of datasets have increased almost linearly over the past decade [15]. Thus, large datasets and neural networks are essential for higher inference accuracy [23]-[25]. Figure 4 demonstrates the increment of the scale of datasets and neural networks over two decades [24], [26]. In contrast to the rapid increase of neural networks and datasets, the capacity of the GPU memory has increased only by a factor of three [23].

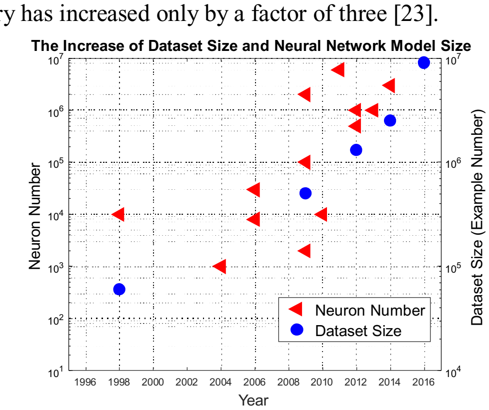

Figure 4: Trend of datasets and DNNs sizes [24].

Building an enormous number of datasets is an extremely time-consuming and tedious task. On the contrary, the human brain is capable of interacting directly with the surroundings and learning from the experience. The learning mechanism is referred to as associative memory learning [14], which enables the neural system to memorize the relationship between two concurrent events [14],

[27]. The associative memory leaning avoids large datasets and can learn from real-world data in Industry 4.0. Furthermore, the self-learning neuromorphic systems built upon associative memory learning potentially have adaptivity and independent working capability, which is the inherent learning mechanism of brains [28].

The investigations on associative memory reveal that two critical features play important roles: synaptic connecting strength modification and distributed data processing [14]. In neural systems, different captured signals, e.g., image and sound, are preprocessed at different regions of the brain. During the learning process, the synaptic connection strength between the sensory and response neurons increases [14].

A pioneering exploration of a brain-like associative memory learning system was conducted by memorizing the relationship between concurrent visual and auditory information [28], [29], in which the associative memory learning is achieved by correlating the probabilistic output scores of artificial neural networks together. Compared to other related works such as in [30], [31], it is the first approach to associate two large-scale neural networks together with a solid biological foundation.

The neuromorphic system built upon the associative memory learning is capable of collecting data constantly from surroundings using smart sensors and learning through its own experiences, which is an essential feature of the autonomous manufacturing in Industry 4.0.

2.3 Reservoir Computing

Another particular neural network that can potentially benefit Industry 4.0 is Reservoir Computing (RC), which belongs to the category of Recurrent Neural Networks (RNN). The outputs of an RNN is not merely determined by its current states, but also the previous states in the time domain. This unique characteristic comes from its recurrent network structure. A similar self-connected configuration also widely exists in the biological neural networks [14]. Its performance metrics outperform traditional RNN methods in nonlinear system identification, prediction, and classification. Reservoir computing has been applied successfully in multifaceted applications including character & speech recognition [32] and generation & prediction of chaotic time series [33].

While the major challenge of RNN is to train all weights within the network, which excessively increases the demand for computational resources. The RC addresses the problem. It adjusts only the weights connecting output layers during the training process, while the weights within the reservoir layer are fixed and untrained. The self-connected neurons within the reservoir have a fixed connecting topology and weights.

Figure 5 illustrates the neural network of RC. It reduces the computational complexity of the learning process to achieve high computational efficiency. The low demand for computational resources is suitable specifically for mobile devices in Internet of Things in Industry 4.0. Several silicon chips were designed for Reservoir Computing [34]-[37]. The computational accuracy of the RC system highly depends on the number of neurons within the reservoir layer, and a large number of neurons increases the hardware complexity of reservoir computing. Recently, it is demonstrated that the computing architecture based on the delay feedback loop in a reservoir is capable of exhibiting rich dynamic behavior. It should be noted that the delay feedback loops are highly hardware-friendly compared with the conventional reservoir system. The reservoir computing system with delay feedback loops is referred to as the time delay reservoir (TDR) computing [35]. In TDR computing, the reservoir layer has only one nonlinear neuron with a self-connected feedback loop.

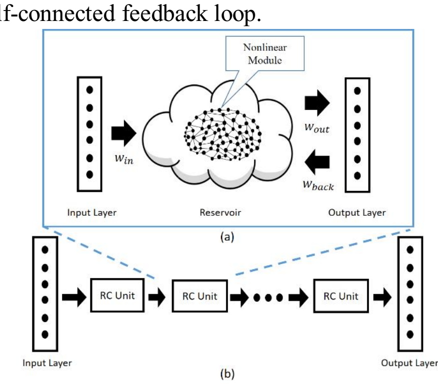

Figure 5: (a) Typical reservoir computing topology (b) the deep reservoir computing topology.

Composability and hierarchy are key to building extreme-scale RC systems and results in significant design complexity. Several works adopt a novel deep RC system constructed by sequencing the conventional reservoirs hierarchically, which further enhances the prediction capability of the system [38]. In general, there is only one reservoir as a primary neural network structure in a typical RC system as illustrated in Figure 5 (a). In order to benefit from the computational capability of deep neural networks of the traditional RC system, we developed a deep RC neural network configuration shown in Figure 5 (b), which hierarchically stacks the basic reservoirs as a building block. The unique structure achieves higher computational efficiency and accuracy simultaneously, which is the essential requirement of low power devices at the mobile side in Industry 4.0.

3 ARTIFICIAL NEURAL NETWORKS FOR INTERNET OF THINGS

So far, ANNs have been used in several applications for IoT, and the authors of [8] identify four major applications of ANNs for IoT systems and devices. First, ANNs enable an IoT system to extract patterns and relationships from the data sent by the IoT devices. The extracted information can be used for various applications such as data compression and recovery. Second, IoT devices adopting ANN-based reinforcement learning algorithms are able to dynamically select most suitable operating conditions, such as the selection of the frequency band and the channel, based on the wireless and users' environments. Third, IoT devices with ANN-based algorithms can identify and classify the data collected from the IoT sensors, and the capability offers various applications such as reduction of the data size to transmit and enhancement of data security. Finally, with the aid of ANN-based algorithms, IoT devices are able to predict the user's behavior, and so the devices can prepare necessary operations in advance. Resultantly, it reduces human supervision to operate IoT devices.

Although ANNs can enhance the capabilities of IoT systems and devices to expand their applications, there are several challenges to overcome [8], [39]. Some of the challenges, but not limited to, are as follows. First, both energy and computational resources are limited for IoT, which necessitates one to tradeoff between energy and accuracy. Second, the collected data of an IoT system may have different types due to such as different operating systems and protocol standards employed. One should consider how to interpret and classify the data correctly for ANN training. Third, the data collected from the IoT devices will be big and all of them may not be related to the task being executed. Hence, ANNs must be able to select suitable data for the task. Fourth, ANNs should consider the trust and security of the data being collected, processed, and processed by IoT devices to share the data.

ANNs are applied for IoT for various purposes. The authors of [40] investigated the good, the bad, and the ugly use of machine learning including ANNs for cybersecurity. They presented numerous good uses, such as the improvement of intrusion detection mechanisms and decision accuracy. They also covered the vulnerabilities of machine learning (bad use) from the perspectives of security, including how machine learning systems can be compromised, misled, and subverted at all stages of the machine learning life-cycle including data collection, pre-processing training, validation, and implementation. Finally, the most concerning and a growing trend is the utilization of machine learning in the execution of cyberattacks and intrusions (ugly use).

The authors in [41] improve the communication quality by mapping IoT networks, primarily a wireless sensor network, to ANNs. They mapped the operations of an ANN onto the communication of an IoT network for simultaneous data processing and data transfer. To minimize the total transmit power and the expected transmit time for the IoT, an ANN is trained to approximate the objective functions, and then the IoT network is mapped to the ANN. The IoT application shows that ANN is an effective tool for network mapping in an IoT.

The authors in [42] simulated eight machine learning algorithms on a supercomputer, including ANN and Deep Learning ANN (DLANN) for classification of human activities, robot navigation, body postures, and movements. Simulation results indicate that DLANN has the best classification accuracy among all the simulated algorithms. An improved classification accuracy could be achieved by increasing the epochs, hidden layers, and neurons. In DLANNs, classification accuracy also depends significantly on its parameter tuning. DLANN has a complex structure, resulting in the longest execution time among all the eight algorithms simulated.

The authors in [43] used the Laguerre neural network-based approximate dynamic programming scheme to improve the tracking efficiency in an IoT network. The proposed scheme is employed in a temperature tracking control system and compared with a multiple layer perceptron (MLP)-based neural network method through the simulation results. The results show that the proposed scheme is more robust and more efficient than the traditional approximate dynamic programming learning method implemented by the MLP-based neural network method.

The authors in [44] developed a streaming hardware accelerator for convolutional neural networks (CNNs) to improve the accuracy of image detection in an IoT network. The work focuses on the optimization of the data-movement flow to minimize data access and achieve high energy efficiency for computation. A new methodology is also proposed to decompose large kernel-sized computation to many parallel small kernel-sized computations. Together with the integrated pooling function, the proposed accelerator architecture can support a one-stop CNN acceleration with both arbitrarily sized convolution and reconfigurable pooling.

The authors in [45] used ANNs for moving target surveillance. They mainly investigated three typical target trajectories such that line, square, and circle. Two types of sensor movement algorithms based on target learning were proposed and compared. One approach is based on a genetic fuzzy tree and the other one based on the neural network. Both algorithms can balance energy consumption and tracking performance. Simulation results show that the genetic fuzzy tree algorithm outperforms the neural network algorithm in tracking error, but it demands more computational cost than that of neural network one.

In summary, a few recent research activities on applications of ANNs for IoT systems and devices are reviewed. ANNs are undoubtedly an important tool for solving a variety of problems in IoT such as communication quality, classification of activities, tracking efficiency, intelligent data analytics, and smart operation.

4 CONCLUSION

The demanding requirements on autonomous and low power operation of the next stage industrialization revolution of Industry 4.0 present great challenges to artificial intelligence. These challenges cannot be addressed through the current data-driven deep learning and traditional von Neumann architecture computers. Thus, we introduce a new path of achieving artificial intelligence that is Neuromorphic Computing. Neuromorphic Computing is a promising cutting-edge approach to implement artificial intelligence by rebuilding the brain. Its low energy budget and self-learning capability of the neuromorphic system will open a new horizon in the era of Industry 4.0. Three critical emerging research directions of neuromorphic computing are introduced in this survey, which are emerging architectures, associative memory learning, and reservoir computing.

REFERENCES

[1] T. Stock and G. Seliger, "Opportunities of sustainable manufacturing in industry 4.0," *Procedia Cirp,* vol. 40, pp. 536-541, 2016.

[2] N. Gronau, M. Grum, and B. Bender, "Determining the optimal level of autonomy in cyber-physical production systems," in *2016 IEEE 14th International Conference on Industrial Informatics (INDIN)*, 2016: IEEE, pp. 1293-1299.

[3] E. A. Lee, "Cyber physical systems: Design challenges," in *2008 11th IEEE International Symposium on Object and Component-Oriented Real-Time Distributed Computing (ISORC)*, 2008: IEEE, pp. 363-369.

[4] L. Atzori, A. Iera, and G. Morabito, "The internet of things: A survey," *Computer networks,* vol. 54, no. 15, pp. 2787-2805, 2010.

[5] A. Ghani, "Neuro-inspired speech recognition based on reservoir computing," in *Advances in Speech Recognition*: InTech, 2010.

[6] K. Xu *et al.*, "Show, attend and tell: Neural image caption generation with visual attention," in *International Conference on Machine Learning*, 2015, pp. 2048-2057.

[7] D. Bahdanau, K. Cho, and Y. Bengio, "Neural machine translation by jointly learning to align and translate," *arXiv preprint arXiv:1409.0473,* 2014.

[8] M. Chen, U. Challita, W. Saad, C. Yin, and M. Debbah, "Artificial neural networks-based machine learning for wireless networks: A tutorial," *IEEE Communications Surveys & Tutorials,* vol. 21, no. 4, pp. 3039-3071, 2019.

[9] M. Agiwal, A. Roy, and N. Saxena, "Next generation 5G wireless networks: A comprehensive survey," *IEEE Communications Surveys & Tutorials,* vol. 18, no. 3, pp. 1617-1655, 2016.

[10] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of things: A survey on enabling technologies, protocols, and applications," *IEEE communications surveys & tutorials,* vol. 17, no. 4, pp. 2347-2376, 2015.

[11] Y. Hu, A. Sanjab, and W. Saad, "Dynamic psychological game theory for secure internet of battlefield things (IoBT) systems," *IEEE Internet of Things Journal,* vol. 6, no. 2, pp. 3712-3726, 2019.

[12] H. An, K. Bai, and Y. Yi, "The Roadmap to Realize Memristive Three-Dimensional Neuromorphic Computing System," in *Advances in Memristor Neural Networks-Modeling and Applications*: IntechOpen, 2018.

[13] K. Roy, A. Jaiswal, and P. Panda, "Towards spike-based machine intelligence with neuromorphic computing," *Nature,* vol. 575, no. 7784, pp. 607-617, 2019.

[14] E. R. Kandel, J. H. Schwartz, T. M. Jessell, S. A. Siegelbaum, and A. Hudspeth, *Principles of neural science*. McGraw-hill New York, 2000.

[15] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*. MIT press, 2016.

[16] H. An, J. Li, Y. Li, X. Fu, and Y. Yi, "Three-dimensional memristor-based neuromorphic computing system and its application to cloud robotics," *Computers & Electrical Engineering,* vol. 63, pp. 99-113, 2017.

[17] D. Drazen, P. Lichtsteiner, P. Häfliger, T. Delbrück, and A. Jensen, "Toward real-time particle tracking using an event-based dynamic vision sensor," *Experiments in Fluids,* vol. 51, no. 5, p. 1465, 2011.

[18] J. L. Krichmar and H. Wagatsuma, *Neuromorphic and brain-based robots*. Cambridge University Press, 2011.

[19] S. Menon, S. Fok, A. Neckar, O. Khatib, and K. Boahen, "Controlling articulated robots in task-space with spiking silicon neurons," in *5th IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics*, 12-15 Aug. 2014 2014, pp. 181-186, doi: 10.1109/BIOROB.2014.6913773.

[20] S. Davies, C. Patterson, F. Galluppi, A. Rast, D. Lester, and S. B. Furber, "Interfacing real-time spiking I/O with the SpiNNaker neuromimetic architecture," in *Proceedings of the 17th International Conference on Neural Information Processing: Australian Journal of Intelligent Information Processing Systems*, 2010: Citeseer, pp. 7-11.

[21] C. Denk, F. Llobet-Blandino, F. Galluppi, L. A. Plana, S. Furber, and J. Conradt, "Real-time interface board for closed-loop robotic tasks on the spinnaker neural computing system," in *International Conference on Artificial Neural Networks*, 2013: Springer, pp. 467-474.

[22] H. An, Z. Zhou, and Y. Yi, "Opportunities and challenges on nanoscale 3D neuromorphic computing system," in *2017 IEEE International Symposium on Electromagnetic Compatibility & Signal/Power Integrity (EMCSI)*, 2017: IEEE, pp. 416-421.

[23] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," *arXiv preprint arXiv:1810.04805,* 2018.

[24] I. Goodfellow, Y. Bengio, A. Courville, and Y. Bengio, *Deep learning*. MIT press Cambridge, 2016.

[25] H. An, M. S. Al-Mamun, M. K. Orlowski, L. Liu, and Y. Yi, "Robust Deep Reservoir Computing through Reliable Memristor with Improved Heat Dissipation Capability," *IEEE Trans. Comput-Aided Des. Integr. Circuits Syst.,* 2020.

[26] C. Sun, A. Shrivastava, S. Singh, and A. Gupta, "Revisiting Unreasonable Effectiveness of Data in Deep Learning Era," *Proceedings of the IEEE International Conference on Computer Vision,* vol. 2017-Octob, pp. 843-852, 2017, doi: 10.1109/ICCV.2017.97.

[27] P. I. Pavlov, "Conditioned reflexes: an investigation of the physiological activity of the cerebral cortex," *Annals of neurosciences,* vol. 17, no. 3, p. 136, Jul 2010, doi: 10.5214/ans.0972-7531.1017309.

[28] H. An, Q. An, and Y. Yi, "Realizing Behavior Level Associative Memory Learning Through Three-Dimensional Memristor-Based Neuromorphic Circuits," *IEEE Transactions on Emerging Topics in Computational Intelligence,* 2019.

[29] H. An, Z. Zhou, and Y. Yi, "Memristor-based 3D neuromorphic computing system and its application to associative memory learning," in *2017 IEEE 17th International Conference on Nanotechnology (IEEE-NANO)*, 25-28 July 2017 2017, pp. 555-560, doi: 10.1109/NANO.2017.8117459.

[30] S. B. Eryilmaz *et al.*, "Brain-like associative learning using a nanoscale non-volatile phase change synaptic device array," *Frontiers in neuroscience,* vol. 8, 2014.

[31] Y. V. Pershin and M. Di Ventra, "Experimental demonstration of associative memory with memristive neural networks," *Neural Networks,* vol. 23, no. 7, pp. 881-886, 2010.

[32] Y. Jin and P. Li, "Performance and robustness of bio-inspired digital liquid state machines: A case study of speech recognition," *Neurocomputing,* vol. 226, pp. 145-160, 2017, doi: 10.1016/j.neucom.2016.11.045.

[33] G. Liang, J. Zhao, F. Luo, S. R. Weller, and Z. Y. Dong, "A Review of False Data Injection Attacks Against Modern Power Systems," *IEEE Transactions on Smart Grid,* vol. 8, pp. 1630-1638, 2017, doi: 10.1109/TSG.2015.2495133.

[34] K. Bai, Q. An, L. Liu, and Y. Yi, "A Training-Efficient Hybrid-Structured Deep Neural Network With Reconfigurable Memristive Synapses," *IEEE Transactions on Very Large Scale Integration (VLSI) Systems,* 2019.

[35] K. Bai, Q. An, and Y. Yi, "Deep-DFR: A memristive deep delayed feedback reservoir computing system with hybrid neural network topology," in *2019 56th ACM/IEEE Design Automation Conference (DAC)*, 2019: IEEE, pp. 1-6.

[36] K. Vandoorne *et al.*, "Experimental demonstration of reservoir computing on a silicon photonics chip," *Nat Commun,* vol. 5, no. 1, pp. 1-6, 2014.

[37] L. Larger, A. Baylón-Fuentes, R. Martinenghi, V. S. Udaltsov, Y. K. Chembo, and M. Jacquot, "High-speed photonic reservoir computing using a time-delay-based architecture: Million words per second classification," *Physical Review X,* vol. 7, no. 1, p. 011015, 2017.

[38] K. Bai, Q. An, and Y. Yi, "Deep-DFR: A Memristive Deep Delayed Feedback Reservoir Computing System with Hybrid Neural Network Topology," *56th ACM/ESDA/IEEE Design Automation Conference (DAC) IEEE,* 2019.

[39] A. Ghosh, D. Chakraborty, and A. Law, "Artificial intelligence in Internet of things," *CAAI Transactions on Intelligence Technology,* vol. 3, no. 4, pp. 208-218, 2018.

[40] F. Liang, W. G. Hatcher, W. Liao, W. Gao, and W. Yu, "Machine Learning for Security and the Internet of Things: The Good, the Bad, and the Ugly," in IEEE Access, vol. 7, pp. 158126-158147, 2019.

[41] N. Kaminski *et al.*, "A neural-network-based realization of in-network computation for the Internet of Things," in *2017 IEEE International Conference on Communications (ICC)*, 2017: IEEE, pp. 1-6.

[42] F. Alam, R. Mehmood, I. Katib, and A. Albeshri, "Analysis of eight data mining algorithms for smarter Internet of Things (IoT)," *Procedia Computer Science,* vol. 98, pp. 437-442, 2016.

[43] X. Luo, Y. Lv, M. Zhou, W. Wang, and W. Zhao, "A laguerre neural network-based ADP learning scheme with its application to tracking control in the Internet of Things," *Personal and Ubiquitous Computing,* vol. 20, no. 3, pp. 361-372, 2016.

[44] L. Du *et al.*, "A reconfigurable streaming deep convolutional neural network accelerator for Internet of Things," *IEEE Transactions on Circuits and Systems I: Regular Papers,* vol. 65, no. 1, pp. 198-208, 2017.

[45] J. Liang, X. Yu, and H. Li, "Collaborative energy-efficient moving in Internet of Things: Genetic fuzzy tree versus neural networks," *IEEE Internet of Things Journal,* vol. 6, no. 4, pp. 6070-6078, 2018.