CS 5463: Survey-based Term Project (Annotated Bibliography)

Topic: A Survey of Spiking Neural Networks and Their Applications

Bibliography of Literature Found: (As of March 21, 2025 – To be updated as literature search continues)

- Ghosh-Dastidar, S., & Adeli, H. (2009). Spiking neural networks. International journal of neural systems, 19(04), 295-308. https://doi.org/10.1142/S0129065709002002

  Summary: This paper reviews the development of spiking neural networks (SNNs), focusing on their evolution as the third generation of neural networks. It discusses how SNNs mimic biological neurons by using precise spike timing for information encoding, which allows for more dynamic and biologically realistic models. The paper also explores various learning algorithms, both supervised and unsupervised, that have been developed for SNNs, highlighting their potential in solving complex time-dependent pattern recognition problems.

- Tavanaei, A., Ghodrati, M., Kheradpisheh, S. R., Masquelier, T., & Maida, A. (2019). Deep learning in spiking neural networks. Neural networks, 111, 47-63. https://doi.org/10.1016/j.neunet.2018.12.002

  Summary: This paper reviews recent advancements in training deep spiking neural networks (SNNs), comparing supervised and unsupervised methods. It highlights the challenges of training SNNs due to the non-differentiability of spike-based activation functions, which complicates the use of backpropagation. The paper also discusses various architectures, such as spiking convolutional neural networks (CNNs) and recurrent SNNs, and their performance on tasks like image and speech recognition, noting that SNNs are more power-efficient but still lag behind traditional deep neural networks in accuracy.

- Bouvier, M., Valentian, A., Mesquida, T., Rummens, F., Reyboz, M., Vianello, E., & Beigne, E. (2019). Spiking neural networks hardware implementations and challenges: A survey. ACM Journal on Emerging Technologies in Computing Systems (JETC), 15(2), 1-35. https://doi.org/10.1145/3304103

  Summary: The paper explores hardware implementations of spiking neural networks (SNNs), focusing on their design, challenges, and potential for low-power, event-driven computation. It discusses various neuromorphic hardware platforms, such as TrueNorth, Loihi, and SpiNNaker, which aim to mimic brain-like computation by integrating memory and processing. The paper highlights the advantages of SNNs, such as energy efficiency and sparsity, but also notes the challenges in training and mapping these networks to hardware. It reviews different learning approaches, including spike-timing-dependent plasticity (STDP) and backpropagation, and compares SNNs to traditional artificial neural networks (ANNs) in terms of performance and energy consumption. The paper concludes that while SNNs show promise for low-power applications, further research is needed to fully exploit their potential, especially in event-driven scenarios.

- Kudithipudi, D., Schuman, C., Vineyard, C. M., Pandit, T., Merkel, C., Kubendran, R., ... & Furber, S. (2025). Neuromorphic computing at scale. Nature, 637(8047), 801-812. https://doi.org/10.1038/s41586-024-08253-8

  Summary: The paper discusses the potential of neuromorphic computing, a brain-inspired approach to designing efficient computational systems, particularly for applications with size, weight, and power constraints. It highlights the key features of neuromorphic systems, such as distributed and hierarchical structures, sparsity, neuronal scalability, and asynchronous communication, which enable energy-efficient and real-time processing. The paper also explores the challenges in scaling these systems, including hardware/software co-design, integration with conventional systems, and the need for standardized benchmarks and tools. Applications in computer vision, robotics, and neuroscience are discussed, emphasizing the potential for neuromorphic systems to revolutionize AI and machine learning. The paper concludes by outlining open questions and future directions for the field, including the development of large-scale test beds and lifelong learning systems.

- Yamazaki, K., Vo-Ho, V.-K., Bulsara, D., & Le, N. (2022). Spiking Neural Networks and Their Applications: A Review. Brain Sciences, 12(7), 863. https://doi.org/10.3390/brainsci12070863

  Summary: The paper reviews spiking neural networks (SNNs), which are inspired by biological neurons and use spikes for communication, making them energy-efficient and suitable for real-time applications. It discusses various neuron models like Hodgkin-Huxley and Leaky Integrate-and-Fire, along with learning methods such as Spike-Timing-Dependent Plasticity (STDP) and ANN-to-SNN conversion. The paper highlights SNN applications in computer vision, including object detection and optical flow estimation, and in robotics for tasks like navigation and locomotion. Despite their potential, SNNs face challenges in training and performance on large-scale datasets compared to traditional deep learning models.

- Sanaullah, Koravuna, S., Rückert, U., & Jungeblut, T. (2023). Exploring spiking neural networks: A comprehensive analysis of mathematical models and applications. Frontiers in Computational Neuroscience, 17. https://doi.org/10.3389/fncom.2023.1215824

  Summary: The paper explores various mathematical models of spiking neural networks (SNNs) to simulate neuron behavior, focusing on their performance, computational efficiency, and biological plausibility. It compares models like LIF, NLIF, AdEx, HH, and others using a synthetic dataset, measuring classification accuracy and performance loss. The AdEx model showed the highest accuracy, while the HH model was the most biologically plausible but computationally expensive. The study highlights the importance of selecting the right model for specific tasks and suggests future research directions like hardware implementation and robustness testing.

- Pietrzak, P., Szczęsny, S., Huderek, D., & Przyborowski, Ł. (2023). Overview of Spiking Neural Network Learning Approaches and Their Computational Complexities. Sensors, 23(6), 3037. https://doi.org/10.3390/s23063037

Summary: The paper reviews various learning approaches for spiking neural networks (SNNs), focusing on their computational complexities and performance on standard hardware like CPUs and GPUs. It categorizes learning algorithms into spike-timing-dependent plasticity (STDP), backpropagation, and ANN-SNN conversion, analyzing their efficiency and memory usage. The study finds that while SNNs are energy-efficient on neuromorphic hardware, they are less efficient on traditional hardware due to the need for multiple time-step simulations. The paper concludes that ANN-SNN conversion methods currently achieve the best performance on benchmark datasets like MNIST and CIFAR-10, but SNNs still face challenges in execution speed and hardware availability.

- Maass, W. (1997). Networks of spiking neurons: the third generation of neural network models. Neural networks, 10(9), 1659-1671. https://doi.org/10.1016/S0893-6080(97)00011-7

Summary: This paper compares the computational power of spiking neuron networks (third-generation models) to earlier neural networks based on McCulloch-Pitts and sigmoidal neurons. It shows that spiking neurons are more efficient, requiring fewer neurons for certain tasks, and better reflect biological neural processing by using spike timing for information encoding. The paper highlights their ability to perform fast, analog computations and provides lower bounds on neuron counts, which shows their superiority over traditional models for specific functions.

- Benjamin, B. V., Gao, P., McQuinn, E., Choudhary, S., Chandrasekaran, A. R., Bussat, J. M., ... & Boahen, K. (2014). Neurogrid: A mixed-analog-digital multichip system for large-scale neural simulations. Proceedings of the IEEE, 102(5), 699-716. https://doi.org/10.1109/JPROC.2014.2313565

Summary: Neurogrid is a neuromorphic system designed to simulate large-scale neural networks in real time, using a mixed analog-digital approach to emulate biological neurons and synapses efficiently. It uses shared electronic circuits for synapses and dendrites, analog circuits for energy efficiency, and a tree network for high throughput. This allows real-time simulation of a million neurons with billions of synapses. The system consumes only 3 watts, making it significantly more energy-efficient than traditional supercomputers for neural simulations. Neurogrid's design allows for scalable and biologically realistic neural simulations, though it currently lacks support for synaptic plasticity.

- Davies, M., Srinivasa, N., Lin, T. H., Chinya, G., Cao, Y., Choday, S. H., ... & Wang, H. (2018). Loihi: A neuromorphic manycore processor with on-chip learning. IEEE Micro, 38(1), 82-99. https://doi.org/10.1109/MM.2018.112130359

Summary: The paper introduces Loihi, a neuromorphic manycore processor designed for spiking neural networks (SNNs) with on-chip learning capabilities. Loihi features 128 neuromorphic cores, supports hierarchical connectivity, and includes programmable synaptic learning rules, enabling efficient spike-based computation. It demonstrates superior energy efficiency in solving optimization problems like LASSO compared to traditional CPUs. The chip's architecture leverages asynchronous design and fine-grained parallelism, making it

suitable for large-scale SNN applications. Preliminary results show significant improvements in energy-delay product and scalability, highlighting its potential for neuromorphic computing.

- Furber, S. B., Galluppi, F., Temple, S., & Plana, L. A. (2014). The spinnaker project. *Proceedings of the IEEE*, *102*(5), 652-665. https://doi.org/10.1109/JPROC.2014.2304638

  Summary: The SpiNNaker project aims to build a massively parallel computer designed to model large-scale spiking neural networks in real time, inspired by the brain's connectivity. The system has a unique communication infrastructure optimized for small data packets that represent neural spikes. It supports up to a million ARM processor cores. It employs an event-driven programming model, where processors remain in low-power states until triggered by events like incoming spikes or timer ticks. The system has been successfully used in various applications, including neural simulations and robotics which shows its flexibility and efficiency in handling real-time neural computations.

- Merolla, P. A., Arthur, J. V., Alvarez-Icaza, R., Cassidy, A. S., Sawada, J., Akopyan, F., ... & Modha, D. S. (2014). A million spiking-neuron integrated circuit with a scalable communication network and interface. *Science*, *345*(6197), 668-673. https://doi.org/10.1126/science.1254642

  Summary: The paper introduces TrueNorth, a neuromorphic chip with 1 million spiking neurons and 256 million synapses designed to mimic brain-like computation. It uses a non-von Neumann architecture that combines memory, computation, and communication in a distributed, event-driven system. The chip is highly energy-efficient, consuming only 63 milliwatts for real-time tasks like multiobject detection. It is scalable and supports various neural network algorithms, making it suitable for future applications in hybrid systems and online learning.

- Schemmel, J., Brüderle, D., Grübl, A., Hock, M., Meier, K., & Millner, S. (2010, May). A wafer-scale neuromorphic hardware system for large-scale neural modeling. In *2010 IEEE international symposium on circuits and systems (iscas)* (pp. 1947-1950). IEEE. https://doi.org/10.1109/ISCAS.2010.5536970

  Summary: The paper presents a wafer-scale neuromorphic hardware system developed under the FACETS project, designed for large-scale neural modeling. It introduces an advanced neuron model, the exponential integrate-and-fire (AdExp), implemented in 180 nm CMOS technology, which operates at accelerated biological time scales. The system integrates neurons and synapses into Analog Network Cores (ANCs) and uses a scalable, low-power communication protocol for event transmission between ANCs. The hardware is complemented by a software framework, PyNN, enabling seamless translation of biological neural models to the hardware, facilitating neuroscience research and applications.

- Diehl, P. U., & Cook, M. (2015). Unsupervised learning of digit recognition using spike-timing-dependent plasticity. *Frontiers in computational neuroscience*, *9*, 99. https://doi.org/10.3389/fncom.2015.00099

  Summary: The paper presents a biologically plausible spiking neural network (SNN) for unsupervised digit recognition using spike-timing-dependent plasticity (STDP). The network, which includes conductance-based synapses, lateral inhibition, and adaptive thresholds, achieves 95% accuracy on the MNIST dataset without using labeled data. The authors demonstrate the robustness of the network by testing four different STDP rules, showing that the combination of mechanisms allows the network to learn prototypical inputs effectively. The network's performance scales well with the number of neurons, and it shows consistent results across different STDP learning rules, suggesting its potential for broader applications in neuroscience and machine learning.

- Mostafa, H., Pedroni, B. U., Sheik, S., & Cauwenberghs, G. (2017, May). Fast classification using sparsely active spiking networks. In *2017 IEEE International Symposium on Circuits and Systems (ISCAS)* (pp. 1-4). IEEE. https://doi.org/10.1109/ISCAS.2017.8050527

  Summary: This paper presents a spiking neural network (SNN) that uses temporal coding to classify MNIST digits efficiently. The network encodes information in the timing of spikes rather than their rate, leading to sparse activity and reduced energy consumption. When implemented on a Field-Programmable Gate Array (FPGA), the network achieves a 3.02% error rate on MNIST, with classification decisions made after 1.3 synaptic time constants and only 5% of hidden neurons spiking on average. The sparse activity minimizes weight lookups and memory traffic, making the system energy-efficient and suitable for low-power hardware applications.

- Srinivasan, G., & Roy, K. (2019). Restocnet: Residual stochastic binary convolutional spiking neural network for memory-efficient neuromorphic computing. *Frontiers in neuroscience*, *13*, 189. https://doi.org/10.3389/fnins.2019.00189

  Summary: ReStoCNet is a memory-efficient Spiking Neural Network (SNN) with binary convolutional kernels and residual connections, designed for neuromorphic computing. It uses Hybrid-STDP (HB-STDP), a probabilistic learning rule combining Hebbian and anti-Hebbian mechanisms, for unsupervised training. The architecture achieves high accuracy (98.54% on MNIST, 66.23% on CIFAR-10) with significant memory compression (39.5× and 21.7×). It is ideal for energy-efficient edge devices and neuromorphic hardware implementations.

- Zhang, M., Gu, Z., Zheng, N., Ma, D., & Pan, G. (2020). Efficient spiking neural networks with logarithmic temporal coding. IEEE access, 8, 98156-98167. https://doi.org/10.1109/ACCESS.2020.2994360

  Summary: This paper introduces an efficient method for converting Artificial Neural Networks (ANNs) to Spiking Neural Networks (SNNs) using Logarithmic Temporal Coding

(LTC) and the Exponentiate-and-Fire (EF) neuron model. LTC encodes activation values logarithmically, reducing the number of spikes needed for computation compared to traditional rate coding. The EF neuron model, designed for digital hardware, performs computations equivalent to ANN neurons with ReLU activation. The method achieves competitive classification accuracy on the MNIST dataset while significantly reducing computational costs, measured by the number of spikes, making it suitable for low-power hardware implementations.

- Zhang, W., & Li, P. (2020). Temporal spike sequence learning via backpropagation for deep spiking neural networks. *Advances in neural information processing systems*, *33*, 12022-12033. https://doi.org/10.48550/arXiv.2002.10085

  Summary: This paper introduces a novel method for training deep Spiking Neural Networks (SNNs) called Temporal Spike Sequence Learning Backpropagation (TSSL-BP), which improves temporal learning precision by breaking down error backpropagation into inter-neuron and intra-neuron dependencies. The method captures inter-neuron dependencies through presynaptic firing times and intra-neuron dependencies by considering the internal evolution of each neuron's state in time, enabling low-latency training with only 5-10 time steps. TSSL-BP achieves state-of-the-art accuracy on multiple image classification datasets, including MNIST, N-MNIST, Fashion-MNIST, and CIFAR10, with up to 3.98% improvement over previous SNN methods. The method also demonstrates sparse firing activity, with over 84% of neurons remaining silent during inference, contributing to energy-efficient computation.

- Rueckauer, B., & Liu, S. C. (2018, May). Conversion of analog to spiking neural networks using sparse temporal coding. In *2018 IEEE international symposium on circuits and systems (ISCAS)* (pp. 1-5). IEEE. https://doi.org/10.1109/ISCAS.2018.8351295

  Summary: This paper introduces a method for converting Analog Neural Networks (ANNs) to Spiking Neural Networks (SNNs) using a temporal coding scheme based on the time-to-first-spike (TTFS). The TTFS approach encodes the activation values of ANN neurons as the inverse of the spike timing in SNNs, reducing the number of spikes and computational costs significantly. The method achieves a 7-10X reduction in operations on the MNIST dataset with less than 1% accuracy loss compared to the original ANN. Three variants of the TTFS method are proposed: a baseline version, one with dynamic thresholds, and another using a clamped ReLU activation function, all of which improve efficiency while maintaining accuracy.

- Han, B., & Roy, K. (2020, August). Deep spiking neural network: Energy efficiency through time based coding. In *European conference on computer vision* (pp. 388-404). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-58607-2_23

  Summary: The paper proposes a novel method for converting Analog Neural Networks (ANNs) to Spiking Neural Networks (SNNs) using a time-based coding scheme called Temporal-Switch-Coding (TSC). This approach encodes pixel intensities using spike times, reducing the number of spikes and computational operations compared to traditional rate-based methods. The TSC-SNN achieves high accuracy on datasets like CIFAR-10, CIFAR-100, and ImageNet with significantly lower inference latency and energy consumption. The method also introduces a threshold balancing technique to minimize accuracy loss during ANN-SNN conversion, making it suitable for deep network architectures like VGG and ResNet.

- Sengupta, A., Ye, Y., Wang, R., Liu, C., & Roy, K. (2019). Going deeper in spiking neural networks: VGG and residual architectures. *Frontiers in neuroscience*, *13*, 95. https://doi.org/10.3389/fnins.2019.00095

  Summary: The paper presents a method for converting deep Analog Neural Networks (ANNs) to Spiking Neural Networks (SNNs) using a novel weight-normalization technique called Spike-Norm. This technique ensures minimal accuracy loss during conversion by considering the actual spiking behavior of SNNs, unlike previous methods that relied solely on ANN activations. The authors demonstrate the effectiveness of their approach on complex datasets like CIFAR-10 and ImageNet using deep architectures such as VGG and ResNet, achieving state-of-the-art SNN performance. Additionally, they show that SNNs exhibit increased sparsity in neural activity as network depth increases, which can lead to significant energy savings in event-driven neuromorphic hardware.

- Rathi, N., Srinivasan, G., Panda, P., & Roy, K. (2020). Enabling deep spiking neural networks with hybrid conversion and spike timing dependent backpropagation. arXiv preprint arXiv:2005.01807. https://doi.org/10.48550/arXiv.2005.01807

  Summary: This paper presents a hybrid training method for Spiking Neural Networks (SNNs) that combines ANN-to-SNN conversion with spike-timing-dependent backpropagation (STDB). The approach initializes SNN weights and thresholds using a converted ANN, then fine-tunes the network with STDB, which uses a novel surrogate gradient based on spike timing. This method reduces the number of time steps required for inference by 10-25x compared to purely converted SNNs, achieving similar accuracy while significantly lowering training complexity. Experiments on CIFAR-10, CIFAR-100, and ImageNet datasets demonstrate the effectiveness of the approach, with top-1 accuracy of 65.19% on ImageNet using only 250 time steps.

- Rueckauer, B., Lungu, I. A., Hu, Y., Pfeiffer, M., & Liu, S. C. (2017). Conversion of continuous-valued deep networks to efficient event-driven networks for image classification. *Frontiers in neuroscience*, *11*, 682. https://doi.org/10.3389/fnins.2017.00682

  Summary: This paper introduces a method for converting Continuous-Valued Deep Networks (ANNs) to Efficient Event-Driven Networks (SNNs) for image classification. The conversion process allows nearly arbitrary CNN architectures, including those with max-pooling, softmax, batch-normalization, and Inception modules, to be transformed into SNNs. The authors demonstrate the conversion of popular CNN architectures like VGG-16 and Inception-v3 into SNNs, achieving state-of-the-art results on MNIST, CIFAR-10, and ImageNet datasets. The key advantage of SNNs is their ability to trade off classification error rate against the number of operations, allowing for significant reductions in computational cost compared to traditional ANNs. For example, the SNN version of LeNet on MNIST achieves a 2x reduction in operations with only a slight increase in error rate.

- Lee, C., Sarwar, S. S., Panda, P., Srinivasan, G., & Roy, K. (2020). Enabling spike-based backpropagation for training deep neural network architectures. Frontiers in neuroscience, 14, 497482. https://doi.org/10.3389/fnins.2020.00119

  Summary: The paper proposes a spike-based backpropagation (BP) algorithm for training deep Spiking Neural Networks (SNNs) using Leaky Integrate-and-Fire (LIF) neurons. The method introduces an approximate derivative for LIF neurons, enabling gradient-based training directly with spike inputs. The authors demonstrate the effectiveness of this approach on deep architectures like VGG and ResNet, achieving state-of-the-art accuracy on datasets such as MNIST, SVHN, and CIFAR-10. The paper also analyzes the sparsity of spike activity, showing that deeper networks exhibit reduced spike counts, leading to energy-efficient inference. Compared to ANN-SNN conversion methods, the proposed approach achieves faster inference with fewer spikes, making it suitable for neuromorphic hardware.

- Wu, Y., Deng, L., Li, G., Zhu, J., Xie, Y., & Shi, L. (2019, July). Direct training for spiking neural networks: Faster, larger, better. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 33, No. 01, pp. 1311-1318). https://doi.org/10.1609/aaai.v33i01.33011311

  Summary: This paper presents a direct training method for Spiking Neural Networks (SNNs) that achieves faster convergence, larger network scalability, and better performance. The authors propose a neuron normalization technique (NeuNorm) to balance neural selectivity and improve accuracy. They also introduce an explicitly iterative version of the Leaky Integrate-and-Fire (LIF) model, compatible with PyTorch, enabling efficient training of deep SNNs. The method achieves state-of-the-art accuracy on neuromorphic datasets (N-MNIST and DVS-CIFAR10) and comparable performance to ANNs on non-spiking datasets like CIFAR10. The approach reduces simulation time significantly, making it feasible to train deep SNNs with fewer time steps.

- Rathi, N., & Roy, K. (2020). Diet-snn: Direct input encoding with leakage and threshold optimization in deep spiking neural networks. arXiv preprint arXiv:2008.03658. https://doi.org/10.48550/arXiv.2008.03658

  Summary: The paper introduces DIET-SNN, a low-latency spiking neural network that optimizes membrane leak and firing threshold using gradient descent to reduce inference latency and improve energy efficiency. It employs direct input encoding, where pixel values are directly applied to the input layer, and the first convolutional layer generates spikes based on learned weights, leak, and threshold. The network is trained using a hybrid approach, starting with ANN-SNN conversion and fine-tuning with error backpropagation, achieving competitive accuracy on CIFAR and ImageNet datasets with only 5 timesteps. DIET-SNN demonstrates 6-18x less compute energy than equivalent ANNs and outperforms other SNN models in latency and energy efficiency due to high activation sparsity and optimized neuron parameters.

- Han, B., Srinivasan, G., & Roy, K. (2020). Rmp-snn: Residual membrane potential neuron for enabling deeper high-accuracy and low-latency spiking neural network. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 13558-13567). https://doi.org/10.48550/arXiv.2003.01811

  Summary: The paper introduces a new type of spiking neuron called Residual Membrane Potential (RMP) neuron, which improves the conversion of Analog Neural Networks (ANNs) to Spiking Neural Networks (SNNs). Unlike traditional "hard reset" neurons that lose information by resetting to a fixed potential, RMP neurons retain residual membrane potential above the threshold, reducing accuracy loss during conversion. The authors demonstrate near loss-less ANN-SNN conversion for deep networks like VGG-16 and ResNet on datasets such as CIFAR-10, CIFAR-100, and ImageNet, achieving state-of-the-art accuracy with fewer inference time-steps. Their threshold balancing scheme ensures optimal performance, making RMP-SNNs more efficient and accurate compared to existing SNNs.

- Lu, S., & Sengupta, A. (2020). Exploring the connection between binary and spiking neural networks. *Frontiers in neuroscience*, *14*, 535. https://doi.org/10.3389/fnins.2020.00535

  Summary: This paper explores the connection between Binary Neural Networks (BNNs) and Spiking Neural Networks (SNNs), focusing on their potential synergy for efficient on-chip edge intelligence. The authors propose a method to train Binary Spiking Neural Networks (B-SNNs) that achieve near full-precision accuracy on large-scale datasets like CIFAR-100 and ImageNet. The key idea is to leverage the binary nature of both BNNs and SNNs, enabling the use of In-Memory Computing hardware accelerators designed for BNNs without significant accuracy degradation. The paper also introduces design-time and run-time optimization techniques to reduce the inference latency of SNNs by an order of magnitude compared to prior work.

- Lee, J. H., Delbruck, T., & Pfeiffer, M. (2016). Training deep spiking neural networks using backpropagation. *Frontiers in neuroscience*, *10*, 508. https://doi.org/10.3389/fnins.2016.00508

  Summary: The paper introduces a novel method for training deep Spiking Neural Networks (SNNs) using backpropagation, addressing the challenge of non-differentiable spike events by treating membrane potentials as differentiable signals. The authors propose a framework that includes fully connected and convolutional SNNs, with techniques for weight initialization, error normalization, and regularization to stabilize training. The method is evaluated on the MNIST and N-MNIST datasets, achieving state-of-the-art accuracy for SNNs, with results comparable to conventional deep neural networks. The approach demonstrates the potential for SNNs to achieve high accuracy with fewer computational operations, making them suitable for energy-efficient, event-driven applications.

- Wu, Y., Deng, L., Li, G., Zhu, J., & Shi, L. (2018). Spatio-temporal backpropagation for training high-performance spiking neural networks. *Frontiers in neuroscience, 12*, 331. https://doi.org/10.3389/fnins.2018.00331

Summary: The paper proposes a Spatio-Temporal Backpropagation (STBP) algorithm for training Spiking Neural Networks (SNNs), which combines both spatial and temporal dynamics to improve performance. The authors introduce an iterative Leaky Integrate-and-Fire (LIF) model suitable for gradient-based training and address the non-differentiability of spike activity by approximating its derivative using various curves. The STBP algorithm is tested on static (MNIST, custom object detection) and dynamic (N-MNIST) datasets, achieving state-of-the-art accuracy without requiring complex training techniques. The results show that incorporating temporal dynamics significantly enhances SNN performance, making it more bio-plausible and hardware-friendly for neuromorphic computing.

- Shrestha, S. B., & Orchard, G. (2018). Slayer: Spike layer error reassignment in time. *Advances in neural information processing systems*, *31*. https://doi.org/10.48550/arXiv.1810.08646

  Summary: This paper introduces SLAYER, a new method for training Spiking Neural Networks (SNNs) that overcomes the challenge of the non-differentiable spike function. SLAYER uses a temporal credit assignment policy to backpropagate errors across both layers and time, allowing it to learn synaptic weights and axonal delays. The authors provide a GPU-accelerated framework for SLAYER, which achieves state-of-the-art accuracy on datasets like MNIST, NMNIST, DVS Gesture, and TIDIGITS. This method is particularly useful for training SNNs on neuromorphic hardware, enabling efficient and low-power machine learning.

- Jin, Y., Zhang, W., & Li, P. (2018). Hybrid macro/micro level backpropagation for training deep spiking neural networks. *Advances in neural information processing systems*, *31*. https://doi.org/10.48550/arXiv.1805.07866

  Summary: The paper introduces a hybrid macro/micro-level backpropagation (HM2-BP) method for training deep Spiking Neural Networks (SNNs). It captures temporal effects using spike-train level post-synaptic potentials (S-PSP) at the micro-level and backpropagates rate-coded errors at the macro-level. This approach directly computes the gradient of the rate-coded loss function, enabling efficient training of deep SNNs. The method achieves state-of-the-art accuracy on datasets like MNIST, N-MNIST, EMNIST, and T146 Speech, outperforming existing SNN training methods.

- Kugele, A., Pfeil, T., Pfeiffer, M., & Chicca, E. (2020). Efficient processing of spatio-temporal data streams with spiking neural networks. *Frontiers in neuroscience*, *14*, 512192. https://doi.org/10.3389/fnins.2020.00439

  Summary: The paper presents a novel method for training Spiking Neural Networks (SNNs) to efficiently process spatio-temporal data streams, particularly for event-based vision tasks. The authors propose modifying Artificial Neural Network (ANN) training using streaming rollouts, which align the temporal delays in ANNs with the propagation delays in SNNs. This approach allows SNNs to achieve state-of-the-art accuracy on event-based datasets like N-MNIST, CIFAR10-DVS, N-CARS, and DvsGesture, while being more energy-efficient than their ANN counterparts. The method leverages temporal skip connections to enable low-latency, approximate network responses that improve over time. The paper demonstrates that SNNs can outperform ANNs in terms of energy efficiency and latency, especially when processing dynamic, event-based data.

- Wu, H., Zhang, Y., Weng, W., Zhang, Y., Xiong, Z., Zha, Z. J., ... & Wu, F. (2021, May). Training spiking neural networks with accumulated spiking flow. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 35, No. 12, pp. 10320-10328). https://doi.org/10.1609/aaai.v35i12.17236

  Summary: The paper introduces a novel backpropagation method called Accumulated Spiking Flow Backpropagation (ASF-BP) for training Spiking Neural Networks (SNNs). The method reduces computational complexity by using accumulated inputs and outputs of spiking neurons over time instead of relying on spike trains. It also introduces an adaptive mechanism to adjust scale factors, reflecting real neuron dynamics. Experiments on MNIST, CIFAR10, and CIFAR10-DVS datasets show that ASF-BP achieves state-of-the-art performance while significantly reducing training time compared to other methods.

- Aayush Ankit, Abhronil Sengupta, Priyadarshini Panda, and Kaushik Roy. 2017. RESPARC: A reconfigurable and energy-efficient architecture with memristive crossbars for deep spiking neural networks. In 54th Annual Design Automation Conference. ACM, 27. https://doi.org/10.48550/arXiv.1702.06064

  Summary: RESPARC is a reconfigurable, energy-efficient architecture using Memristive Crossbar Arrays (MCAs) for accelerating Spiking Neural Networks (SNNs). It combines in-memory processing and event-driven computation to achieve significant energy savings (up to 500×) and higher throughput (up to 300×) compared to CMOS-based systems. The architecture supports various SNN topologies (MLPs, CNNs) and optimizes MCA size for different technologies. RESPARC is ideal for neuromorphic computing, offering scalable and energy-efficient solutions for recognition tasks like MNIST, SVHN, and CIFAR-10.

- Alireza Bagheri, Osvaldo Simeone, and Bipin Rajendran. 2018. Adversarial training for probabilistic spiking neural networks. In IEEE 19th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC). IEEE, 1–5. https://doi.org/10.48550/arXiv.1802.08567

  Summary: The paper investigates the sensitivity of Spiking Neural Networks (SNNs) to adversarial examples and proposes a robust training mechanism to enhance their resilience. The study focuses on a two-layer SNN with rate and time encoding, as well as rate and first-to-spike decoding. The authors demonstrate that SNNs are vulnerable to white-box adversarial attacks, where small perturbations in the input spike trains can significantly degrade classification accuracy. To mitigate this, they introduce a robust training method that incorporates adversarial examples during training, improving the SNN's performance under adversarial conditions. The results show that first-to-spike decoding is more resilient to certain types of attacks compared to rate decoding, and that robust training significantly enhances the SNN's robustness to adversarial perturbations.

- Gupta, A., & Long, L. N. (2007, August). Character recognition using spiking neural networks. In 2007 International Joint Conference on Neural Networks (pp. 53-58). IEEE. https://doi.org/10.1109/IJCNN.2007.4370930

  Summary: The paper presents a spiking neural network (SNN) model for character recognition using a two-layered structure with integrate-and-fire and active dendrite neurons. The network employs spike-timing-dependent plasticity (STDP) for training and uses lateral inhibitory connections to enforce a winner-take-all mechanism. The model successfully recognizes most characters in a 48-character set, even with increased resolution and added noise. The network adjusts weights for off-pixels to zero during training, demonstrating robust learning and recognition capabilities.

- Liang, L., Hu, X., Deng, L., Wu, Y., Li, G., Ding, Y., ... & Xie, Y. (2021). Exploring adversarial attack in spiking neural networks with spike-compatible gradient. IEEE transactions on neural networks and learning systems, 34(5), 2569-2583. https://doi.org/10.48550/arXiv.2001.01587

  Summary: This paper explores adversarial attacks on Spiking Neural Networks (SNNs), addressing challenges like gradient-input incompatibility and gradient vanishing. The authors propose a Gradient-to-Spike (G2S) converter and a Restricted Spike Flipper (RSF) to generate spike-compatible adversarial examples. Experiments show 99%+ attack success rates on benchmarks like MNIST and CIFAR-10, demonstrating SNNs' robustness compared to ANNs. The work highlights the importance of loss function and firing threshold tuning for effective attacks.

- Neftci, E. O., Mostafa, H., & Zenke, F. (2019). Surrogate gradient learning in spiking neural networks: Bringing the power of gradient-based optimization to spiking neural networks. IEEE Signal Processing Magazine, 36(6), 51-63. https://doi.org/10.1109/MSP.2019.2931595

  Summary: The article explores the challenges of training Spiking Neural Networks (SNNs), which are hindered by their binary and dynamical nature, particularly in deep architectures with hidden layers. To address these issues, the authors introduce Surrogate Gradient (SG) methods, which provide a continuous relaxation of the nonsmooth spiking nonlinearity, enabling gradient-based optimization. These methods are applied in various contexts, such as feedback alignment, local three-factor learning rules (e.g., SuperSpike), and spike-time-based learning, offering efficient and scalable training solutions for SNNs. The article highlights the potential of SG methods to bridge machine learning, neuroscience, and neuromorphic computing, while emphasizing the need for further research to optimize activation functions and generalize to continuous-time dynamics.

- Wang, X., Lin, X., & Dang, X. (2020). Supervised learning in spiking neural networks: A review of algorithms and evaluations. Neural Networks, 125, 258-280. https://doi.org/10.1016/j.neunet.2020.02.011

  Summary: The paper reviews supervised learning algorithms for Spiking Neural Networks (SNNs), focusing on their ability to process temporal and spatiotemporal data using

biologically plausible spiking neurons. It categorizes algorithms based on network architecture (single-layer, multilayer feed-forward, and recurrent SNNs) and learning mechanisms (gradient descent, synaptic plasticity, spike train convolution, etc.). The paper evaluates the performance of these algorithms using qualitative criteria such as spike train learning ability, online/offline processing, locality, stability, and applicability to different neuron models. It also proposes a taxonomy for supervised learning algorithms and suggests future research directions, including online learning, hybrid SNNs, and hardware implementation.

Course Website: https://github.com/asifulhoque23/utsa-cs5463-course-website