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

Topic: A Survey of Spiking Neural Networks and Their Learning Strategies

Annotated Bibliography:

1. 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 computing capacity of spiking neuron networks (third-generation models) to older neural networks built with 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.

2. 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 analyzes the advancement of SNNs, emphasizing their significance as a next step in the evolution of neural network models. It discusses how SNNs work like biological neurons by encoding information with precise spike timing, 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, which shows how useful they could be for solving difficult temporal pattern recognition problems.

3. 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 SNNs, which are based on 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. Although SNNs have potential, they encounter obstacles in training and performance on large-scale datasets in comparison to traditional deep learning models.

4. 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 SNNs to replicate the behavior of neurons, 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 demonstrated the highest level of accuracy, while the HH model was the most biologically plausible but computationally expensive. The study emphasizes the significance of selecting the appropriate model for specific tasks and recommends future research directions, such as hardware implementation and robustness testing.

5. 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 SNNs, focusing on their ability to handle temporal and spatiotemporal data with biologically plausible spiking neurons. It categorizes algorithms based on network architecture (single-layer, multilayer feed-forward, and recurrent SNNs) and learning mechanisms (gradient descent, spike train convolution, synaptic plasticity, 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 suggests future research guidelines, such as hardware implementation, hybrid SNNs, and online education, and proposes a classification scheme for supervised learning algorithms.

6. 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 by spike-timing-dependent plasticity (STDP). The network consists of conductance-driven synapses, lateral restriction, and adjustable thresholds. Without the use of labeled data, it obtains an accuracy of 95% on the MNIST dataset. 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 demonstrates consistent performance scaling as the number of neurons increases. It offers consistent results across different STDP learning rules, suggesting its potential for broader applications in neuroscience and machine learning.

7. 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 SNNs, which focus on their computational complexities and performance on standard hardware like CPUs and GPUs. It divides learning algorithms into three groups, analyzing their efficiency and memory usage: backpropagation, spike-timing-dependent plasticity (STDP), and ANN-SNN conversion. 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 standard datasets such as CIFAR-10 and MNIST, but SNNs still face challenges in execution speed and hardware availability.

8. 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 discusses the latest advances in training deep SNNs, comparing supervised and unsupervised methods. It shows how difficult it is to train SNNs because of the non-differentiability of spike-based activation functions, which complicates the use of backpropagation. The paper discusses various architectures, such as spiking convolutional neural networks (CNNs) and recurrent SNNs. The paper further describes how they performed on tasks such as image and speech recognition. It indicates that SNNs are more power-efficient but still lag behind traditional deep neural networks in accuracy.

9. 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: This paper discusses how difficult it is to train SNNs, since they are binary and dynamic, particularly in deep architectures with hidden layers. To address these issues, the authors introduce Surrogate Gradient (SG) methods, which enable the nonsmooth spiking nonlinearity to be continuously relaxed. It enables 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.

10. 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 technique to train deep SNNs using backpropagation, addressing the challenge of non-differentiable spike events by processing membrane potentials as separate 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 tested on the MNIST and N-MNIST datasets, and it obtains the highest level of 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, which makes them appropriate for event-driven applications that use little power.

11. 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 to train SNNs, which includes both temporal and spatial dynamics to improve performance. The authors present an iterative Leaky Integrate-and-Fire (LIF) model suitable for gradient-based training and address the spike activity, which is non-differentiable, by estimating its derivative from various curves. The STBP algorithm is tested on static (MNIST) and dynamic (N-MNIST) datasets. It achieves state-of-the-art accuracy without requiring complex training techniques. The results indicate that incorporating temporal dynamics significantly enhances SNN performance, making it more biologically plausible and hardware-friendly for neuromorphic computing.

12. 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 deep SNNs training. 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. Spike-train-level post-synaptic potentials (S-PSPs) are used to capture temporal dynamics at the micro-level, while rate-coded errors are backpropagated at the macro-level to guide learning. This method calculates the gradient of the rate-coded loss function directly, which makes it possible to train deep SNNs effectively. The method obtains state-of-the-art accuracy on datasets like MNIST, N-MNIST, EMNIST, and T146 Speech, outperforming existing SNN training methods.

13. 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) to train SNNs. The method reduces computational complexity by aggregating the inputs and outputs of spiking neurons across time steps 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 demonstrate that ASF-BP obtains state-of-the-art performance while significantly reducing training time compared to other methods.

14. 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 introduces a conversion technique from deep Analog Neural Networks (ANNs) to Spiking Neural Networks (SNNs) by employing a novel weight normalization approach 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 show that their method works on challenging datasets like CIFAR-10 and ImageNet through deep architectures like VGG and ResNet, getting state-of-the-art SNN performance. Additionally, they indicate that SNNs exhibit increased sparsity in neural activity as network depth increases. This method can help event-driven neuromorphic devices save a lot of energy.

15. 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 presents a conversion strategy from traditional analog deep networks to spiking neural networks to classify images. The conversion process allows nearly arbitrary CNN architectures to be transformed into SNNs. The authors show how to transform well-known CNN designs like VGG-16 and Inception-v3 into SNNs, getting the best results on the MNIST, CIFAR-10, and ImageNet datasets. SNNs' main advantage is their ability to balance classification error rate and quantity of operations, which allows 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.

16. 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 article proposes a technique to convert Analog Neural Networks (ANNs) to Spiking Neural Networks (SNNs) utilizing a temporal coding scheme focused on the time-to-first-spike (TTFS). The TTFS method represents ANN neuron activations as inverse spike times 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 a 1% drop in accuracy in comparison 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.

17. 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: The paper presents a hybrid approach to train SNNs by integrating artificial-to-spiking network conversion with spike-timing-dependent backpropagation (STDB). The approach initializes SNN weights and thresholds using a converted ANN, which is then optimized via STDB with a novel surrogate gradient that depends on spike timing. This method minimizes the inference time steps by 10-25x compared to purely converted SNNs, achieving similar accuracy while significantly lowering training complexity. The approach shows its efficiency across CIFAR-10, CIFAR-100, and ImageNet datasets, obtaining 65.19% top-1 accuracy on ImageNet in only 250 time steps.

18. 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: This paper explores neuromorphic computing, a method that takes design inspiration from the brain to develop effective computing infrastructure, with a focus on those applications that have power limitations. It draws attention to the fundamental characteristics, 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.

19. 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 analyzes the adversarial sensitivity of SNNs and proposes a robust training mechanism to enhance their resilience. The study models a two-layer SNN architecture featuring both rate and time-based encoding and rate and first-to-spike decoding strategies. 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.

20. 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 investigates adversarial attacks on SNNs, highlighting difficulties like gradient-related limitations such as gradient incompatibility and vanishing gradients. The authors introduce two components, such as 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.

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