On the Future of Training Spiking Neural Networks

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Abstract: Spiking Neural Networks have obtained a lot of attention in recent years due to their close depiction of brain functionality as well as their energy efficiency. However, the training of Spiking Neural Networks in order to reach state-of-the-art accuracy in complex tasks remains a challenge. This is caused by the inherent non-linearity and sparsity of spikes. The most promising approaches either train Spiking Neural Networks directly or convert existing artificial neural networks into a spike setting. In this work, we will express our view on the future of Spiking Neural Networks and on which training method is the most promising for recent deep architectures.

1 INTRODUCTION

Deep Learning (DL) is becoming more and more influential both in our current daily lives as well as in future research. There have been remarkable achievements in a variety of application areas, such as computer vision (Krizhevsky et al., 2012), text processing (Vaswani et al., 2017), autonomous driving (Chen et al., 2017) and robotics (Andrychowicz et al., 2019).

Unfortunately, as the complexity of the applications grows, so does the size of the neural network and the energy resources required during training and inference. This leads not only to a higher carbon footprint but also to limited applicability on mobile devices. It has been shown that costs grow roughly in proportion to the demand for computing power, so we are inevitably heading towards the point where DL is no longer sustainable (Thompson et al., 2021). On the other hand, the brain uses only a fraction of the resources compared to a computer while performing comparable or even more complex tasks and additionally managing general functions of the body (Balasubramanian, 2021). This demonstrates that a great deal of optimization and innovation is still required to truly exploit the full potential of DL and neural architectures.

One possible approach is the usage of Spiking Neural Networks (SNNs) (Gerstner and Kistler, 2002), which depict the biological functionality of the brain more closely than traditional Artifical Neural Networks (ANNs). Spiking neurons communicate by means of spikes, which can be represented solely on the basis of ones and zeros. Therefore, theoretically no multiplications with synaptic weights like in ANNs are necessary. The multiplication with zero results automatically in zero and a multiplication with one in the weight itself, which only requires a single memory read-out. Additionally, the inherent sparsity of the spikes leads to a generally decreased amount of computations in the network, since only the arrival of spikes induces computations in the neuron. For these reasons SNNs have the advantage of a lower energy consumption during inference and training compared to ANNs.

In theory, SNNs have been shown to possess the same expressive power as ANNs (Maass and Markram, 2004). However, practically there are still many hindrances in the training of SNNs, so that in the majority of cases they cannot reach the performance capability of ANNs at the time being.

There are generally three ways to obtain a trained SNN: Biological, conversion from a pre-trained ANN, and direct training. The biological approach typically leads to local optimization rules that are difficult to extend to deep networks, (Nunes et al., 2022). This can be avoided by utilizing an existing ANN and converting it into a SNN, since this principle can be applied to a variety of modern architectures (Rueckauer et al., 2017). However, restrictions are often imposed on the ANN and the conversion is in any case an approximation, so that the resulting SNN usually suffers from lower performance. There are also obstacles associated with the direct training, since the spiking functional is non-differentiable and thus the

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successful gradient descent method is not directly applicable.

In this work, we will explore and compare the advantages and disadvantages of these training paradigms especially with regard to their use in future real-world applications. This encompasses their practicality in very deep neural networks as well as their applicability for complex datasets. We are convinced, that the future of SNNs lies in the direct training, due to its capability to train deep networks, its greater variability concerning the encoding of input data and its consideration of internal temporal relationships of SNNs.

2 RELATED WORK

2.1 Spiking Neural Networks

The general architecture of SNNs is analogous to the structure of ANNs (Gerstner and Kistler, 2002). The crucial difference lies in the functionality of the spiking neurons, which implement biological processes in a more detailed way. Spiking neurons have a membrane potential U that grows in response to external stimuli. If a certain threshold θ is exceeded, the neuron fires and thus transmits a spike via outgoing synapses. However, since it is very improbable that all spikes arrive at a neuron simultaneously, there are additional temporal dynamics, which maintain the membrane potential over a short period of time.

In experiments on nerves in frogs, these dynamics were found to be comparable to those in a simple resistor–capacitor circuit (Brunel and van Rossum, 2007). Inspired by this, the simple Leaky Integrate-and-Fire (LIF) neuron model is nowadays often used in DL implementations for SNNs. A discrete approximation of the LIF model can be described in the following way (Wu et al., 2019):

$$U[t] = \underbrace{\beta U[t-1]}_{\text{decay}} + \underbrace{WX[t]}_{\text{input}} - \underbrace{S_{out}[t-1]\theta}_{\text{reset}}, \quad (1)$$

with β as the decay rate of the membrane potential, $WX[t]$ as the weighted input spikes and $S_{out}[t] \in \{0,1\}$ as the generated output spike. The exponential decay of the membrane potential sustains the incoming spike information for a short amount of time, while also preserving the non-correlation between spikes at too distant time steps. Especially when ANNs are converted to SNNs, this decay is often disregarded which results in the Integrate-and-Fire (IF) neuron model. Furthermore, in case the neuron fires the membrane potential gets reset by subtracting the threshold. Outgoing spikes are generated, when the membrane potential reaches the threshold:

$$S_{out}[t] = \begin{cases} 1, \text{ if } U[t] > \theta \\ 0, \text{ otherwise.} \end{cases} \quad (2)$$

However, this functionality is non-differentiable, meaning that gradient descent is not applicable as in conventional ANNs. For this reason, the training of SNNs is still an ongoing research topic.

2.2 Data Handling

Since the calculations in SNNs are based on spikes, input data such as intensity values in images must be converted to a spike format. This is especially relevant in the context of converting ANNs, since the input encoding needs to abide certain restriction for the converted SNN, which will be further explained in Section 2.3. The two main approaches for encoding floating points into spikes are temporal and rate encoding.

The temporal encoding stores the information within the timing of a single spike. For image data this means that a high pixel intensity is encoded in an earlier spike, while a low intensity pixel is mapped to a later spike. In addition, a logarithmic mapping is applied to mimic processes in the retina (Dehaene, 2003; Arrow et al., 2021). The main advantage of temporal encoding is the low energy consumption, since the input data is extremely sparse and thus requires minimal computations and memory access. However at the same time, the sparsity leads to an insufficient amount of training signals and can therefore result in dead neurons. Furthermore, this encoding has a poor error tolerance, since similar classes can fire at the same time and no additional time step is taken into account in order to compensate for this. Additionally, it remains ambiguous which property should be described by an earlier spike time. A high intensity pixel, for example, may only describe background information of an image and therefore initially provide little information to the neural network. This becomes particularly problematic with more complex input data and has been insufficiently addressed, as most approaches have only considered simple datasets such as MNIST (Lecun et al., 1998).

Rate coding on the other hand stores the information in the number of spikes N over a period of time. Accordingly, in the most common rate coding scheme, the average firing rate v over the time window T can be defined as follows:

$$v = \frac{N}{T}. \quad (3)$$

This is typically modeled with a Poisson distribution with a mean event rate proportional to the normalized pixel intensity (Nunes et al., 2022). The occurrence of rate coding in biological processes has been demonstrated in several studies, (Adrian and Zotterman, 1926). It has the advantage of having a high error tolerance, since numerous incoming spikes can excite a neuron that previously failed to fire. Furthermore, in output neurons, subsequent output spikes can compensate for errors and make it easier to distinguish classes. In addition, a large number of spikes leads to many training signals and accordingly a stronger gradient signal. However, this results in a trade-off in terms of higher energy consumption and training time due to increased computational operations. Rate-coding is especially important for conversion algorithms. These methods create SNNs based on pre-trained ANNs based on the assumption, that the input data will be fed into the converted SNN in a rate-coded manner.

Recently, several SNN methods have started to use the direct encoding scheme (Zenke and Vogels, 2021), in which the floating point values of the input data are fed directly into the network. This means that the first neuron layer is used to convert these values into spikes and thus adopt the functionality of body sensors. The advantage of this approach is that the encoding does not have to be explicitly predefined in a manual manner and is instead learned by the network.

Biologically, different types of information encoding in spikes exist in the brain (Izhikevich, 2003). For this reason, it is important to study different types of encoding that find a balance between trainability and energy efficiency. In theory, there are an infinite number of ways to represent information in the form of spikes, there is no necessity to limit oneself only to temporal or rate encoding.

The most natural type of input for SNNs is event-based data, since it already consists of binary events and is further sparse and asynchronous. For example, Dynamic Vision Sensor (DVS) cameras can be used to detect intensity changes above a threshold in an asynchronous manner (Gallego et al., 2022). For traditional ANNs, processing this type of data is challenging because they perform synchronous computations. Thus pre-training an ANN directly with event data for later conversion into a SNN becomes challenging, (Deng et al., 2019).

2.3 Training of SNNs

Despite all the successes of DL, the brain still remains the reference point due to its comprehensive precision and efficiency. For this reason, there is still a great research effort to understand the exact processes in the brain. Nevertheless, it is still not possible to find the exact mechanism that allows the brain to learn complex patterns and abstract thinking.

For traditional ANNs, the most successful training algorithm is backpropagation (Rumelhart et al., 1986), which led to extraordinary successes for ANNs in classification and recognition tasks (Krizhevsky et al., 2012). However, this cannot be applied to SNNs due to the non-differentiable nature of spike emergence. Thus, the training of SNNs is still a challenging open research question. Currently, there are three main types of training algorithms for SNN: Biological, conversion based on a pre-trained ANN, and direct training.

2.3.1 Biological Training

From a biological perspective, synaptic coupling in the brain is strengthened when there is a positive correlation between pre- and postsynaptic neuron activity (Morris, 1999). Similarly, synaptic depression occurs when there is decorrelation of activity. This phenomenon is described as Spike Timing Dependent Plasticity (STDP) and is often used to train SNNs as a more closely biological representation of the brain. In this approach, synaptic weights are strengthened when the presynaptic neuron fires just before the postsynaptic neuron (Bi and Poo, 1998). This, however, results in local updates during the training, making it challenging to work with deep network architectures.

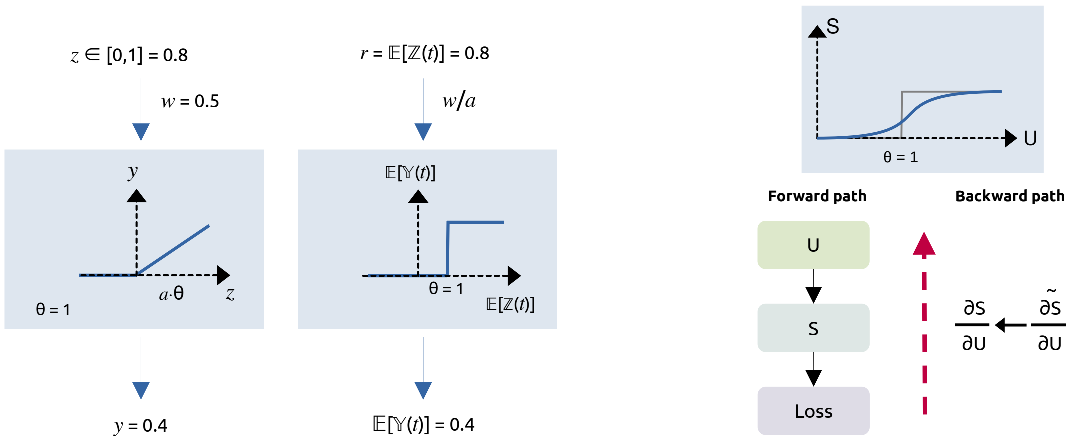
2.3.2 ANN to SNN Conversion

In order to transfer the progress in training and architecture design of ANNs directly to SNNs, SNNs can be constructed based on pre-trained ANNs (Diehl et al., 2015). Thus, the obstacle of non-differentiability is circumvented and state-of-the-art ANN approaches can be directly adopted. In theory, the IF neuron can be seen as an unbiased estimator of the ReLU activation, which is illustrated in Figure 1a. Based on the definition of SNNs, the following relationship at the input layer is obtained between the firing rate r and the input $z \in [0,1]$ (Rueckauer et al., 2017):

$$r = \frac{z}{\theta} - \frac{V_T - V_0}{T\theta}. \tag{4}$$

with V_T and V_0 as the membrane potentials at $t = T$ and $t = 0$, respectively. Using $z = a \cdot \theta$ with a as the ReLU activation, $\theta = 1$ and an infinite number of time steps T, we get the following relationship between the firing rate and the estimator for the ReLU activation (Rueckauer et al., 2017):

$$r = a, \ (a > 0) \tag{5}$$



(a) Conversion of an ANN into a SNN.

(b) Direct training.

Figure 1: Visual comparison of the conversion of a pre-trained ANN into a SNN (a) and the direct training (b) using $\frac{\partial \tilde{S}}{\partial U}$ as a surrogate gradient during the backward pass.

In a similar manner, these concepts can be extended for higher layers. The basic idea of most conversion approaches is then to approximate the inner floating point values of the network using rate coding and to adjust the ANN parameters so that the input values to each layer lie in the range of $[0,1]$. Therefore, the weights of the ANN have to be normalized, using the maximum activation for each layer based on the whole training dataset, with a threshold of 1 (weight-normalization) (Sengupta et al., 2019). An equivalent approach is also to adjust the threshold by a normalization factor while the weights are taken directly (threshold-balancing) (Sengupta et al., 2019). The conversion approach by Stöckl and Maass (2021) is instead based on the temporal encoding of the input data. However, their approach necessitates a modification of the spiking neuron definition. This means, the pre-trained ANN architecture as well as the input encoding have to abide to a number of restrictions for any of the currently available conversion methods to work properly.

2.3.3 Direct Training

The advantage of using spikes directly is that a gradient can be calculated even if no spike occurred. For this, the backpropagation is calculated over the different paths in the computational graph, which can extend over several time steps, for example by using Back-Propagation Through Time (BPTT) (Werbos, 1990). However, to calculate the gradient from the loss to the network parameters, one must apply the chain rule, which contains the non-differentiable term $\frac{\partial S}{\partial U}$, as described in Section 2.1. The solution to this is the use of a surrogate gradient function during the backward pass, which is shown in Figure 1b. This function approximates the gradient from the application of the heaviside operator for U during the forward pass.

Most often, variations of the following surrogate functions centered around the threshold are used (Zenke and Vogels, 2021): *Sigmoid*, *fast sigmoid*, *triangular*, or *arctan* function. However, the exact understanding of the influence of the biased gradient estimator is still missing. Nevertheless, the use of surrogate gradient is the current state-of-the-art for native training of SNNs (Nunes et al., 2022). The great advantage of surrogate gradients is that they solve the dead neuron problem. Conventionally, the gradient $\frac{\partial S}{\partial U} = 0$ when no spike is fired. Thus, the corresponding neuron is not included in the loss and no learning can take place on its weights. However, the application of an approximation can overcome this obstacle by a non-zero estimate, so that we can obtain a gradient over all layers.

2.4 Related Evaluation Studies

Previous comparisons between training methods for SNNs focus on their application to very simple datasets and architectures. For example, Deng et al. (2019) compare directly trained as well as converted SNNs and ANNs on MNIST (Lecun et al., 1998), CIFAR10 (Krizhevsky, 2009) and their event driven variant, N-MNIST (Orchard et al., 2015) and DVS-CIFAR10 (Li et al., 2017). Their results suggest that directly trained SNNs are best suited for frame-free spike data. However, the datasets treated do not match the complexity in real world applications, so we focus on the ImageNet (Deng et al., 2009) dataset and

ResNet (He et al., 2016) architecture in our work. The papers by Rathi et al. (2020) and Rueckauer et al. (2017) deal with more complex networks and data, but they only compare the accuracy of the ANN training with the converted SNN, whereas our work includes the direct training of deep SNNs. Other papers list the results of different training methods for SNNs (Meng et al., 2022; Datta et al., 2021), but mainly focus on performance difference and not inherent restrictions by the training methods like we do in this paper.

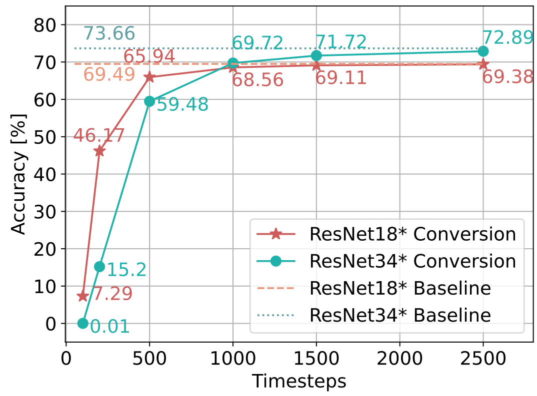


Figure 2: Results of the evaluation of the converted SNN for the pre-trained networks ResNet18* and ResNet34* using different numbers of time steps.

3 EXPERIMENTS AND RESULTS

3.1 Network Architecture

The focus of our work lies on the applicability of deep SNNs for real-world scenarios. This is why, we use the ResNet architecture (He et al., 2016) for our experiments. It is based on building blocks which include a shortcut connection for identity mapping. Accordingly, it reduces the degradation problem for very deep networks that are necessary for complex tasks. In addition, the architecture for ImageNet includes a maxpooling layer before the building blocks and finally an average pool and fully connected layer. We use Resnet18 and ResNet34, which are the 18 and 34 layer version of the residual architecture. Furthermore, the algorithm for conversion requires that the ANN architecture does not contain maxpooling. Therefore, we remove the maxpooling from the original ResNet architecture (Resnet18* and ResNet34*) and use these networks for the conversion into a SNN.

3.2 Training Details

Because of its challenging real world setting, we will test the different SNN training methods for classification on the ImageNet (Deng et al., 2009) dataset. It contains about 1.3 million training images and 50,000 validation images with 1000 classes and is therefore complex enough to represent a real-world scenario. Moreover, we normalize the images and crop them to a size of 224×224 pixels, randomly during training and centered during inference. As optimizer we use Stochastic Gradient Descent (SGD) and apply a batch size of 32 with a starting learning rate of 0.00125. The learning rate decays by $\gamma = 0.1$ after each 30 epochs. We train for a maximum of 90 epochs. We further apply the cross-entropy loss for all algorithms and evaluate the top-1 accuracy for the classification on ImageNet.

Our work puts its focus on the comparison of the basic concepts and limitations behind different training methods for SNNs and evaluates their potential applicability in future real-world scenarios, which does not only depend on the achieved accuracy. For this reason, we will use basic algorithms, that showcase the general advantages and disadvantages of the direct training of SNNs and the conversion based on ANNs. For the direct training method, we therefore use gradient descent and overcome the non-differentiability of the spiking neuron formulation by using the *arctangent* as a surrogate gradient during the backward pass. To convert the trained ANN into a SNN, we use the algorithm by Rueckauer et al. (2017). It addresses the handling of batch normalization, whose parameters can be absorbed in other parameter layers. In addition, the weights and biases of the ANN are normalized by the maximum output tensor of each layer.

3.3 ANN to SNN Conversion

In Figure 2 it can be seen that the accuracy after conversion depends considerably on the number of time steps t used for the simulation of the converted SNN. After 100 time steps, the converted networks can only achieve about 10 percent of the performance of the original ANN for Resnet18*. For the deeper network Resnet34*, the converted SNN is almost not able to perform any classification after 100 steps. This shows that the deeper the network architecture is, the more accurate the approximations of the floating point values of the ANN must be. Accordingly, more time steps for the rate coding are necessary to achieve a certain performance. Only after 1000 time steps are the converted SNNs able to reach a similar accuracy compared to the baselines of the pre-trained ANNs.

Table 1: Top-1 classification accuracy on the ImageNet evaluation dataset for the directly trained and converted SNNs as well as for the pretrained ANNs.

Architecture	NN type	Training	t	acc1 [%]
ResNet18	ANN	direct	-	67.00
ResNet34	ANN	direct	-	70.70
ResNet18*	ANN	direct	-	69.93
ResNet34*	ANN	direct	-	73.66
ResNet18	SNN	direct	5	47.99
ResNet18	SNN	direct	10	53.51
ResNet34	SNN	direct	5	44.73
ResNet34	SNN	direct	10	52.71
ResNet18*	SNN	conversion	2500	69.38
ResNet34*	SNN	conversion	2500	72.89

However, the loss of performance compared to the original network becomes negligible with 2500 time steps. It can be seen that there is an exponential relationship between the number of time steps and the accuracy. Nonetheless, the goal of the conversion methods is the approximation of the original ANN and will thus most likely result in a reduced performance for the SNN.

3.4 Direct Training vs Conversion

Table 1 shows the comparison of the results for the original ANNs, the converted SNNs and the directly trained SNNs. In this case, it can also be seen that removing the maxpooling layer actually increases the performance of the networks. Accordingly, the results from the conversion based on the Resnet18* and ResNet34* architectures are not directly comparable to the directly trained SNNs, which all contain the maxpooling layer as in the original architecture.

The directly trained SNNs with $t = 5$ have about 20 percentage points lower accuracy than the original networks, since the networks are very deep and the error of the surrogate gradient adds up across the layers. However, for the directly trained ResNet18 and ResNet34 with $t = 10$, the performance increases significantly by about 6 and 8 percent, respectively, compared to their training runs with 5 time steps, which shows that a higher number of time steps leads to an increased performance.This is due the higher number of potential output spikes, which are produced for every time step and help distinguishing similar classes. Moreover, the resulting gradient becomes more meaningful, since the behavior of all neurons is considered over all time steps. Thus, there is further potential for direct training if the number of time steps is increased even further, especially for deeper architectures.

The results of the conversion with $t = 2500$ are clearly superior compared to the directly trained SNN. However, as evident from Figure 2, for the conversions of the ResNet18* and Resnet34* architecture about 200 and 500 time steps, respectively, are necessary to achieve similar results to the directly trained SNNs. Therefore, the conversion methods result in a latency that is about two orders of magnitudes higher compared to the direct training.

4 DISCUSSION

Training SNNs is still a challenging task, especially for deep and complex network architectures. Biological algorithms such as STDP currently handle only local updates based on the correlation of the behaviors of neighboring neurons. Since no end-to-end training of SNNs is possible in this way, the error is propagated and accumulated through all network layers. This makes it impossible to train deep state-of-the-art network architectures. Nonetheless, there is great potential in the biological approach, as it can lead to more understanding of the brain's processes.

However, until the global training processes in the brain are discovered, direct training of SNNs is the best option. Direct training takes into account the temporal component of spikes and thus exploits their true potential. This makes them particularly attractive for applications with event-based data, since they allow an asynchronous and sparse input with which traditional ANNs have to struggle. The only problem is the discontinuity in the spiking function, which prevents gradient descent from being applied directly. However, this can be solved by approximating the gradient by a surrogate function, especially since it has been shown that even random feedback in small networks leads to good results (Lillicrap et al., 2016). Furthermore, the direct training of SNNs is the only method, which has the future potential to fully take advantage of neuromorphic chips for inference as well as for training. This is relevant in terms of energy efficiency in the whole process of creating applications of SNNs in real world scenarios. On synchronous hardware such as GPUs, simulated training of SNNs tends to have increased energy consumption due to the multiple time steps over which spikes are fed into the network.

The inherent temporal component of spiking data cannot be exploited in a conversion from ANNs to SNNs, since the ANN must be trained on synchronous hardware and further struggles with very sparse inputs. Moreover, the converted SNN is necessarily only an approximation of the original ANN with the goal of increasing energy efficiency. However, the temporal component is completely ignored, so that for example event data cannot be entered directly. Furthermore, other pruning methods are available in order to reduce energy consumption of ANNs, which means there is no necessity to enforce the constraints of the SNN architecture in order to reach this goal. In addition, the original floating point values must be approximated by the firing rate during the conversion. This means, that an enormous latency is required to achieve a suitable accuracy, which in turn increases the energy consumption and the inference time extremely. This makes converted SNNs almost unusable for complex real world scenarios and direct training of SNNs should be preferred.

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