FAKULTA APLIKOVANÝCH VĚD
ZÁPADOČESKÉ UNIVERZITY
V PLZNI

STUDENTSKÁ VĚDECKÁ KONFERENCE 2021

Use of Spiking Neural Networks

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1 Introduction

Spiking neural networks (SNNs) can be thought of as the next generation of artificial neural networks. Unlike widely applied analog neural networks (ANNs), SNNs do not use continuous activation functions and instead share information via trains of discrete action potentials - spikes. This property makes them great candidates for biologically plausible simulations as well as energy-efficient replacements of ANNs. However, in their current state, SNNs are still in early development and require more research to be applicable.

This work aims to contribute to the research of spiking neural networks by applying them to selected brain-computer interface (BCI) experiments and image datasets for classification tasks.

2 Datasets and Experiments

The presence of spikes fundamentally changes the way a spiking neural network can be trained. Conventional backpropagation cannot be used directly, and thus many alternative methods have appeared. Here, the two used training approaches were a conversion from a fully trained analog network to a spiking one and Surrogate Gradient (SG) learning proposed by Netfci et. al (2019). SG replaces the "real" gradient of the loss function, which is not usable for training due to the discrete nature of spikes, with a surrogate one that has favourable properties for efficient backpropagation. In total, three classification experiments were performed using four datasets:

1. Classification of Large Multi-Subject P300 Dataset created by Mouček et. al (2017)
2. Classification of BNCI Horizon dataset created by Reichert et. al (2020)
3. Classification of the MNIST and Fashion MNIST datasets

The conversion approach often yields better results than other methods and thus was used in the first two experiments containing BCI data, which are typically harder to classify than image datasets. The first experiment used a slightly modified convolutional neural network (CNN) from the paper by Vařeka (2020), who also used it on the same P300 dataset (though without conversion to an SNN). Thirty iterations of Monte Carlo cross-validation (CV) were performed, each comprising 30 epoch training of the analog CNN and its subsequent conversion to an SNN. The converted SNN was tested with several spiking parameters such as firing rate scaling and synaptic smoothing (turning them "on" typically improves performance). The second experiment adopted a similar approach as the first one. Two different CNN models were used - one from the previous P300 experiment, while the other used 5×5 and 3×3 convolutional layers

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with average pooling layers in between. The entire BNCI dataset was applied in 10-fold CV and both analog CNNs were converted to their spiking variants.

Finally, the third experiment used SG learning instead of an ANN conversion as both MNIST and Fashion MNIST are relatively easy to perform well on and it was interesting to see the effect of direct training. Unfortunately, it was not possible to easily implement any type of special layers such as convolutional. Therefore, only fully connected deep spiking networks were considered. Overall, four different models were trained for 30 epochs, where the best performing one for both datasets comprised two hidden layers with 256 and 128 units.

3 Results

Three different experiments with spiking neural networks were performed. The result of each experiment is shown in Table 1. Unsurprisingly, the highest accuracy was attained by the SNN model in the third experiment on MNIST and Fashion MNIST. This shows that surrogate gradient can be a viable method for training since the models were simple, fully connected networks, and more complex models would likely perform better. The results from the first experiment are also promising. The SNN even achieved marginally better accuracy than the original model from Vařeka (2020). The second experiment was however unsuccessful and neither of the CNN models was able to classify the data. Both analog CNN models did not score any better than a random choice, and thus, the converted SNNs performed poorly as well.

Experiment	**Dataset**	**Training**	**Epochs**	**Model**	**Accuracy** [%]
1	P300	Conversion	30	CNN	64.96
2	BNCI Horizon	Conversion	30	CNN (2 conv. layers)	52.31
2	BNCI Horizon	Conversion	30	CNN (from exp.1)	52.04
3	MNIST	SG	30	Dense - 2 hidden layers	97.09
3	Fashion MNIST	SG	30	Dense - 2 hidden layers	85.52

Table 1: Results from each performed experiment

References

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