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A single-hidden-layer neural network for the classification of spike-waveforms

L. M. Meyer[1*], T. Schanze[1] and F. Samann[1,2]

[1] *Technische Hochschule Mittelhessen - University of Applied Sciences, Giessen, Germany*

[2] *Department of Biomedical Engineering, University of Duhok, Kurdistan Region-Iraq*

[*] *Corresponding author, email: luca.maximilian.meyer@lse.thm.de*

Abstract: The goal of this work is to demonstrate that a simple neural network can classify and distinguish Gaussian white noise and eight different noisy spike-waveforms with different correlation levels. For small noise levels up to 10% (σ_{noise}= 10%max(x)), where max(x) is the maximum spike-amplitude) classification performance is flawless. Results for strong noise, e.g., σ_{noise}=50%max(x), reveal that our network struggles with two things: distinguishing correlated data and reliably detecting noise. To apply our approach to real brain data, the problem of spike collisions must be solved in the future.

I. Introduction

Classical spike sorting, the process of identifying and sorting extracellularly recorded action potentials (also called spikes) with regards to their timing and putative neuron, can be divided in the substeps of filtering, spike detection, alignment, feature extraction and clustering [1]. Since neurons generate characteristic spike-waveforms, corresponding assignments are feasible [1]. The desired outcome of spike sorting are labeled timestamp sequences indicating the activities of neurons. Efficient spike sorting is highly reliant on automated solutions as extracellular recordings take on incomparably high values, especially with high density multi-channel probes. In the last years, many research groups developed NNs to handle different subproblems in spike sorting, such as spike detection or feature extraction, but end-to-end solutions are also emerging [2], [3]. Therefore, complex deep learning networks like convolutional neural networks, long-short-term memory networks, and even combinations of several types with many hidden layers are mostly used [2], [3] but simpler networks also got applied recently to tackle special tasks in the spike sorting pipeline. In [4], a single-hidden-layer network was developed to classify extracellularly recorded signals as spikes or noise. However, the presented NN does not distinguish between different spike-waveforms and thus is not a sorter. The utility of neural network-based spike sorting extends beyond neuroscience, as it could be used to process large streams of data generated in modern brain-computer interfaces.

In this work, we show that complex network architectures are not strictly necessary to perform basic spike sorting. We present an approach using a simple NN that not only distinguishes between spike-waveforms from different groups but can also discriminate spikes and noise to some extent. This can help to improve the overall performance of spike sorting, since prior spike detection is not guaranteed to be error-free.

II. Material and methods

The present noise level in extracellular recordings highly depends on the used measuring and filter technique. Although other research groups used data with maximum noise of 20-40% [3], we investigated noise up to 50% to impede classification and impose limits. All noise levels in this paper refer to their standard deviation with respect to the maximum spike amplitudes.

II.I. Data preparation

Eight different groups of center-aligned spikes, each containing 17 samples, were generated manually using Python. With 2% amplitude variability for the spikes, we tried to mimic the real-world problem of cortical single-unit measurements. For the same reason, Gaussian white noise (GWN) was added to all spikes. 50 samples were chosen for the noise signals, which can also be seen as the size of the classification window. Therefore, we created six different datasets, as noise levels between 0% and 50% with a 10% gradation were considered. Different noise levels were not mixed within setups. Each dataset contains 1000 spikes per group. In addition, 1000 signals of pure GWN were generated to test whether the network detects spike-waveforms present in the signal or not. This leads to a total number of nine different classes, which can be seen in Fig. 2. They are directly corresponding to the output layer activations of the NN, as the highest activation indicates the predicted class. We split the dataset for training and testing of the NN with a ratio of 5:3. 10% of the training set were used for validation during training.

II.II. Relevant data properties

It is important to note that we designed the spike-waveforms with different levels of correlation. Since the eight spike-waveforms are four basic signals and their respective reflections, there is a complete inverse correlation between them for noise-free signals. While the groups 1-6 show high correlation, spikes from groups

Table 1: Precision (P) and Recall (R) of the eight spike groups and a pure signal of GWN for different noise levels

Class	SPIKE 1		SPIKE 2		SPIKE 3		SPIKE 4		SPIKE 5		SPIKE 6		SPIKE 7		SPIKE 8		GWN	
Metric	P	R	P	R	P	R	P	R	P	R	P	R	P	R	P	R	P	R
σ_{noise} = 20%	99%	100%	99%	99%	96%	99%	96%	99%	98%	100%	98%	100%	100%	100%	99%	100%	100%	88%
σ_{noise} = 30%	96%	96%	95%	97%	89%	96%	89%	95%	91%	99%	90%	99%	97%	100%	96%	100%	100%	56%
σ_{noise} = 40%	90%	91%	90%	91%	83%	88%	83%	88%	82%	95%	81%	95%	93%	100%	93%	100%	98%	33%
σ_{noise} = 50%	83%	85%	82%	85%	77%	85%	76%	80%	72%	80%	72%	89%	90%	98%	90%	98%	90%	17%

7 and 8 show low correlation to other groups respectively. If the noise level increases, the correlation decreases over the entire dataset. This effect is presented in Fig. 1 in the form of heatmaps for the average correlation values between all considered spike groups. We generated both high and low correlated spikes to test whether there are differences in classification performance.

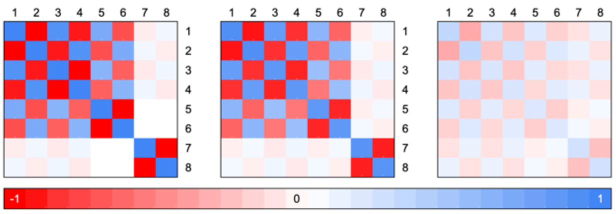

Figure 1: Heatmaps of the averaged correlation matrices between the eight spike groups at three different noise levels (left: zero noise, middle: 10% noise, right: 50% noise).

II.III. Neural network

Python and TensorFlow were used to build our NN. For the hidden layer the ReLU activation function was used, while the output layer utilizes the Softmax activation function. The network architecture can be seen in Fig. 2. The NN was trained in a supervised way over 50 epochs separately for each considered noise level and tested respectively. For compiling, the categorical cross-entropy loss function was utilized together with the Adam optimizer. EarlyStopping regularization was used to minimize overfitting. If there was no reduction in loss within five consecutive epochs the model stopped computing.

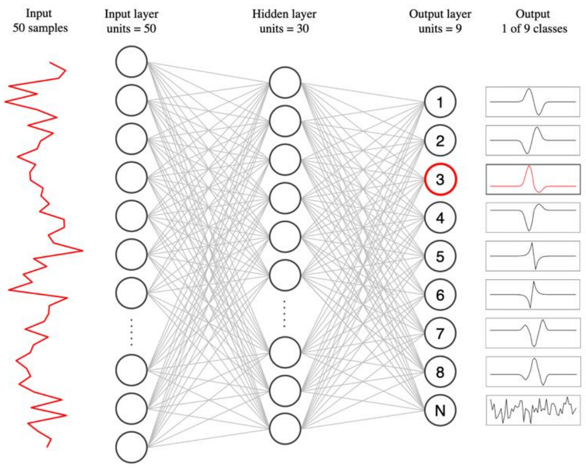

Figure 2: A spike-waveform from group 3 with present noise of 50% gets classified. Each unit in the output layer represents one of nine classes (groups 1-8 and pure GWN (N)).

III. Results and discussion

To obtain reliable results, we averaged over 100 runs. Accuracy was between 89% and 100%, depending on the respective noise level, and only small differences between classes were observed. To get better insights into the false positive and false negative predictions, precision and recall were calculated class-wise (Tab. 1.) Here, only results for noise levels from 20% to 50% are presented, as classifications for lower noise levels led to flawless results. Tab 1. clearly shows that the NN generalized better on uncorrelated waveforms (groups 7 and 8). Moreover, recall revealed that classification performance for GWN highly decreased with its level. Here, it must be mentioned that spikes from groups 5 and 6 were predicted in 44% of the false negative cases at a noise level of 50%. Similar results were observed at lower noise levels, as their sharp peaks resemble those of pure GWN.

In order to apply our NN to real brain data, further improvements are necessary. In extracellular recordings, multiple neurons often fire simultaneously near the electrode, leading to temporal overlap. However, this cannot be handled by our network at this stage. In addition, it would be beneficial if the NN could detect and classify unknown spikes that are not part of the training set, which also is not possible yet.

IV. Conclusions

The obtained results clarify three important things. 1) It is possible to distinguish pure GWN and noisy spikes with our NN. 2) While the NN can distinguish between different spikes and noise for small noise levels, it tends to classify noise as spikes above noise of 20%. (Tab. 1, cf. recall). A high sampling rate in combination with appropriate band-pass filtering may reduce misclassifications, since sharp spike-waveforms can thus be reduced. 3) Correlated data are more difficult for the NN to classify than uncorrelated data, which is a problem, as spikes are often highly correlated. The results show that a complex network structure is not necessary to do basic spike classification. However, more complex data, e.g., real brain recordings of highly active neural clusters with many overlapping spikes, may require further adjustments to our NN, i.e., more hidden layers, to perform efficient spike sorting..

Author's statement

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