Brain Modelling Coding Project

MNIST Input Applied to the Izhikevich Network

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1 Context

The basis of our project is the implementation of a network of Izhikevich Neurons, seen during the lectures. The single Izhikevich neuron is characterized by two state variables u and v, the former representing the membrane "recovery" and the latter the membrane potential. We also have four parameters: a, b, c and d, which control the state variables in different ways. Since we are dealing with a network, a number of inhibitory and excitatory neurons is also defined, in a ratio of approximately 1 to 4, due to the structure of the mammalian cortex. These neurons are then connected to each other with a certain synaptic strength S, different for the two classes. [1]

2 Goals

The objective of our work was to study the variations in the network response when provided with static visual inputs belonging to different classes. To do so, we kept the original visualization methods and built an input pipeline which would allow us to rate-code static images into a suitable input current which could be fed to the neurons [2], [3], [4].
Moreover, since we deemed useful to verify the meaningfulness of the model responses, we implemented a Classifier that, given the model's response, could predict the label of the image used as input.

3 Results

We examined the behaviour of the network in response to the stimuli we specified before. The presentation of our results includes three main components, that are:

- the visual stimulus;
- the spikes' Raster plot, which yields the temporal representation of neuronal activity, with neuron indices on the vertical axis and activation times on the horizontal axis;
- the plot of the average firing rate of the neurons, highlighting the dynamic patterns generated by the network in response to the stimulus.

The scenarios we covered put an emphasis on simpler characteristics of the stimulus, such as changes in brightness, light distribution, and intensity. They are the building blocks which characterize the model responses to the various input's classes, through their different combinations.

The most explicative results are yielded by the Raster plots that are built from the model output, in which precise firing patterns are visible. Generally, for all inputs, the neurons seem to display rhythmic behaviour, that is, oscillations, even though weaker inputs (i.e. darker or irregular images) make it quickly degenerate into an almost random firing pattern. Discerning by eye the label of the input image solely from the model output is a difficult task. However, we could observe a unique correlation between the distribution of bright pixels in the image and the indexes of the firing neurons. If a number of non-black pixels appear along the same y coordinate, there will be stronger responses from excitatory neurons at indexes inversely proportional to it. For example, if a white horizontal line is present in the upper portion of the image, there will be a stronger response from low-index neurons, which can include bursting of populations.

Regarding the deep neural network, we used a simple LSTM classifier, given the sequence nature of the response of neurons. The performance of the classifier was more than satisfying, with an accuracy higher than 75% on a subset of 10000 images. The model successfully matched the spike patterns with the corresponding labels the majority of the times, showing that the Izhikevich Network actually exhibits meaningful, label-specific behaviour, which in turn can be decoded. We did not search for the most optimal parameters as it was not the objective of the project. Surely a model trained on the whole dataset, bigger or more refined, would have performed even better.

References

[1] Eugene M. Izhikevich, "Simple Model of Spiking Neurons", IEEE TRANSACTIONS ON NEURAL NETWORKS, Vol. 14, No. 6, p. 1569-1572, November 2003

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[3] Jiankun Chen, et al., "SAR Image Classification Based on Spiking Neural Networks through Spike-Time Dependent Plasticity and Gradient Descent", ISPRS Journal of Photogrammetry and Remote Sensing, p. 1-43, June 16 2021

[4] Robert Max Slick, "Neural Coding: Generating Spike Trains For Images Using Rate Coding", Jan 1 2022, Available: https://medium.com/@rmslick/neural-coding-generating-spike-trains-for-images-using-rate-coding-6bb61afef5d4