A Machine Learning approach to Neural Information Decoding of Spike Train Distances in the Peripheral Nervous System

Abstract

Decoding the neural signal has proved to be an elusive goal. We explore the use of sequence analysis algorithms to identify repeating patterns of spike train distances and found that they could be associated to the stimulus in the rat peripheral system with good results. The use of these algorithms is very common in genomics and proteomics for genetic sequence analysis but rarely applied to neural systems analysis. We are convinced that with proper tuning they could yield useful results.

1 Introduction

Spike Train Distance is a metric that measures the sequence of action potentials emitted by individual neurons [1]. This edit-length metric is applicable to event sequences and yield distances that convey the meaning of the neural code and depending on how the measurements are made, they could be analogous to the symbol sequence used to analyzed EEG data and more common in the analysis of genetic sequences [2, 3]. This approach has been used for almost 50 years in the study of the structure of DNA to identify similar patterns in the amino acid sequence but only until recently these sequence analysis algorithms have been applied to neuroscience [1].

1.1 Motivation

The main idea is that the postsynaptic effects of a spike may depend strongly on the recent activity at that synapse, as suggested by some authors [12, 13, 14] and the meaning of a spike train depends on the specific interval sequence pattern. If we can identify the patterns associated to a stimulus and the variations as the stimulus changes, we will be partially decoding the communication signals within the brain and opening the door to a wide variety of applications connecting devices to the brain and allowing the brain to control these devices. Several applications for health and entertainment could become a reality such as prosthesis control or sensing in a videogame.

1.2 Related work

Victor and Purpura [4, 5] used the spike interval distance metric to study how the monkey brain responded to visual stimuli, and the results were promising but inconclusive. In [6], the authors study the Low-Threshold Mechanoreceptors of the rat Peripheral Nervous System to find the structure of the message using a set theory framework that could successfully identify repeating patterns in the sequence of intervals. Other authors [7, 8, 9, 10] have highlighted the importance of studying spike train distances to decode the neural signal.

2 Methodology

In this research, the raw bioelectrical signals were acquired in-vivo from the sciatic nerve of the rats. Proper protocols for handling living stock were rigorously followed. The signals were pre-processed using the T-Distributed EM algorithm for detecting the spikes in the recording, as provided by the ®Plexon acquisition system. Next, the distance between spikes was computed and converted to a symbol, depending on the length of the distance. The histogram obtained from the data showed a right-skewed distribution with more occurrences of shorter inter spike distances. The stimulus was a pressure of 4 grams of force and later it was varied to 6, 8, 10 and 15 grams of force during a two minutes period. This procedure was repeated with 8 different patients. Fig. 1 illustrates the data acquisition process.

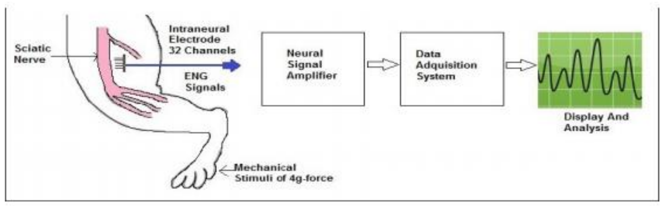

Figure 1. Neural signal acquisition.

3 Discussion and future work

Initial results were encouraging since we were able to identify patterns of two, three and even four symbols that were repeated and correlated with the stimulus. The analysis also showed that the number of bins in the histogram had a strong effect in the determination of the symbols representing the different distances, and consequently, on the patterns it could identify. Further studies are required to determine the appropriate number of bins for the histogram. Also, experiments are being conducted with sequence analysis algorithms such as the Needleman-Wunsch to find variations were a near perfect match is found and how much the distance varies from the original pattern. In later test, we will be using deep recurrent networks to explore if these models could be useful for decoding the neural signal.

References

[1] Victor, J. D. and Purpura, K. P. (2010) Spike Metrics. In S. Grün, and S. Rotter (eds.), *Analysis of Parallel Spike Trains*, pp. 129-156. Boston, MA: Springer.

[2] Wu, L., and Gotman, J. (1998). Segmentation and classification of EEG during epileptic seizures. *Electroencephalography and Clinical Neurophysiology, 106(4),* 344–356. DOI:10.1016/s0013-4694(97)00156-9

[3] Needleman, S. B., and Wunsch, C. D. (1970) A general method applicable to the search for similarities in the amino acid sequence of two proteins. *Journal of Molecular Biology 48*, 443–453

[4] Victor, J. D., and Purpura, K. P. (1996) Nature and precision of temporal coding in visual cortex: a metric space analysis. *Journal of Neurophysiology 76*, 1310–1326.

[5] Victor, J. D., and Purpura, K. P. (1997) Metric-space analysis of spike trains: theory, algorithms and application. *Network 8*, 127–164.

[6] Nolasco-Jaúregui, O. and Leyva-Montiel, L. (2017). Headers and payloads inside of nervous system as like as digital communication protocols? *International Journal of Biomedical Engineering and Science 4*(1), 25-36. DOI: 10.5121/ijbes.2017.4103.

[7] Chicharro, D., Kreuz, T. and Andrzejak, R. G. (2011). What can spike train distances tell us about the neural code? *Journal of Neuroscience Methods 199,* 146-195.

[8] Panzeri, S., Harvey, C. D., Piasini, E., Latham, P.E., and Fellin, T. (2017). Cracking the neural code for sensory perception by combining statistics, intervention, and behavior. *Neuron 91*(3), 491-507.

[9] Bialek, W., Rieke, F., de Ruyter van Steveninck, R. R., and Warland, D. (1991). Reading a neural code. *Science 252*, 1854-1857.

[10] Nirenberg, S., and Latham, P. E. (2003). Decoding neuronal spike trains: How important are correlations? *Proceedings of the National Academy of Sciences 100*, 7348-7353.

[11] Jacobs, A. L., Fridman, G., Douglas, R. M., Alam, N. M., Latham, P. E., Prusky, G. T., and Nirenberg, S. (2009). Ruling out and ruling in neural codes. *Proceedings of the National Academy of Sciences 106*, 5936-5941.

[12] Dan, Y., and Poo, M. M. (2004) Spike timing-dependent plasticity of neural circuits. *Neuron 44*, 23–30.

[13] Markram, H., Lubke, J., Frotscher, M., and Sakmann, B. (1997) Regulation of synaptic efficacy by coincidence of postsynaptic APs and EPSPs. *Science 275*, 213–215.

[14] Sen, K., Jorge-Rivera, J. C., Marder, E., and Abbott, L. F. (1996) Decoding synapses. *Journal of Neuroscience 16*, 6307– 6318.