Artificial Neural Microcircuits as Building Blocks for Neuromorphic Systems

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Summary. Artificial Neural Networks (ANNs) are the most widely employed forms of neuromorphic computation. However, unlike the biological systems they draw inspiration from, the current standard is for ANNs to be structurally homogeneous. This is at odds with research evidencing that structure plays a significant role in supporting learning capability and function of the brain. In this paper, an alternative approach inspired by biological Neural Microcircuits is suggested. The conceit of assembling ANNs using a catalogue of Artificial Neural Microcircuits, and a methodology to assemble said catalogue, is articulated; before showing the results of initial work to produce such a catalogue.

Introduction

The current state-of-the-art for ANNs is focused on large, topologically homogeneous feed forward or recurrent networks which are tailored for specific applications either via machine learning or evolutionary algorithms [7] [2]. Some less widely used alternatives do exist, generally focused on the use of evolutionary approaches to produce complex topologies from scratch [8].

Advances in neuroscience paint a picture of biological nervous systems that possess a much more compartmentalised architecture; built from various "fundamental processing units" called Neural Microcircuits, which work together both hierarchically and in parallel [3, 6].

This work presents the first steps towards drawing more inspiration from the latter kind of architecture: articulating a means of employing novelty search to produce a catalogue of Artificial Neural Microcircuits, which can then be used as "off-the-shelf" components to fashion larger, application specific Spiking Neural Networks.

Generating Artificial Neural Microcircuits

To assemble a catalogue of Microcircuits, it is necessary to: (i) generate a selection of candidate Microcircuits; (ii) assess them based on some criteria; and (iii) use the assessment to select which Microcircuits would be useful components. An overview of this flow is shown in figure 1, and is elaborated upon below.

In order to allow the Microcircuits in the catalogue to be somewhat substrate independent, rather than assembling possible Microcircuits out of discreet neurons, Neural Circuit Motifs are used instead; allowing for the injection of some additional biological domain knowledge [1, 6]. Several of these motifs are then combined to form larger Microcircuits, which are represented using a trio of connection matrices: (i) one for external inputs; (ii) one for internal connections; and (iii) a final array for outputs.

Microcircuits are assessed by feeding them a stimulus pattern, or a set of stimulus patterns, producing outputs in the form of spike trains. By comparing these spike trains, though the use of the Bivariate

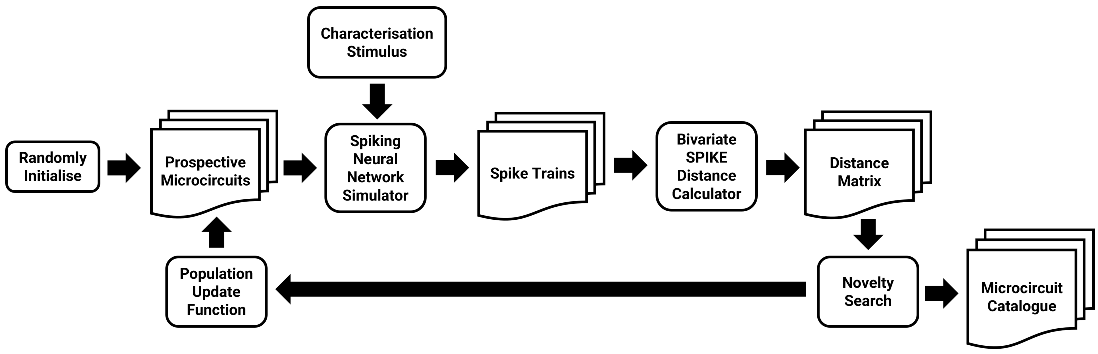

Figure 1: The methodology used to generate the catalogue of Artificial Neural Microcircuits.

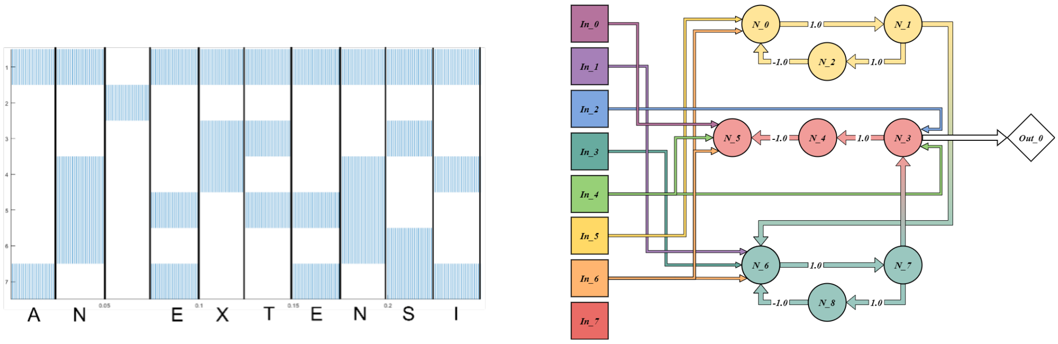

Figure 2: *Left:* Input text encoding 466. *Right:* Illustration of Microcircuit 466.

SPIKE-Distance metric [4], it is possible to build up a matrix of behavioural difference measurements. These values can then be used to calculate a novelty value for each Microcircuit, allowing for a Novelty Search algorithm [5] to be used to select which individuals are to be added to the Microcircuit catalogue.

Initial Experiments

To test the methodology, a test run was performed, using spike trains derived from UTF-8 character encoding of a text sample as 8-input stimulus (shown on the left of figure 2). From a total pool of 5,000 Microcircuits, the novelty search function transferred 50 to the catalogue. The behaviours of these 50 were investigated to determine what functionality they possessed, in particular whether their outputs showed a strong correlation to a given patterns of inputs. While a variety of behaviours occurred, a clear validation of the concept can be found in Microcircuit 466, shown on the right of figure 2.

Produced in the fifth iteration, with 9 neurons across 3 motifs, Microciruit 499 displayed a very strong correlation with the four punctuation mark characters in the sample text used (Space, Comma, Dash and Stop)—without having explicitly searched for this functionality. A Microcircuit with such a behaviour has a clear use as a component of a larger Neuromorphic system. It is easy to see how a catalogue of similar Microcircuits could be used to assemble a network able to completely parse UTF-8 text streams, but of course it's also possible to go further.

The exact same Microcircuits could be used as part of a network that takes in handwritten characters, with other kinds of Microcircuits forming the interface between the character images and the character recognisers; or in a completely different application where the 8-bit patterns they recognise are some other stimuli of interest, providing a set of versatile building blocks with innate capabilities, with no need to train them, for text processing.

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