

Leveraging brain-adaptation principles to increase radiation resistance of neuromorphic space hardware

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ABSTRACT

This research sets out to test whether principles of brain adaptation can be leveraged to increase the radiation resistance of neuromorphic space hardware. Neuromorphic architectures provide energy efficient platforms for AI applications in space. Structural similarities between neuromorphic architectures and the brain may allow them to benefit from brain-inspired design on the topic of damage

recovery. Space environments can provide challenging conditions with significant radiation exposure, that may damage neuromorphic space hardware. To explore approaches to mitigate such damages, a simulated radiation test with- and without a brain inspired implementation adaptation is investigated. These adaptations are applied to a spiking neural network (SNN) implementation of a distributed

minimum dominating set approximation algorithm by Alipour et al. The experiment is performed using Intel's Lava 0.3.0 Framework. With radiation induced neuron death probabilities of 25%, adaptation increased SNN robustness, compared to no adaptation. At lower neuron death probabilities, no difference is observed.

METHODOLOGY

Algorithm Selection

The MDS approximation as presented by Alipour et al., is specified in the following Algorithm:

Input: Connected, planar, triangle-free graph of size n .

Output: Set of nodes that form a minimum total dominating set.

– In the first round, each node v_i chooses a random number $0 < r_i < 1$ and computes its weight $w_i = d_i + r_i$ and sends w_i to its adjacent neighbours.

– In the second round, each node v marks a neighbour vertex v_i whose weight w_i is maximum among all the other neighbours of v .

– for m rounds do

– Let x_i be the number of times that a vertex is marked by its neighbour vertices, let $w_i = x_i + r_i$

– Unmark the marked vertices.

– Each vertex marks the vertex with maximum w_i among its neighbour vertices.

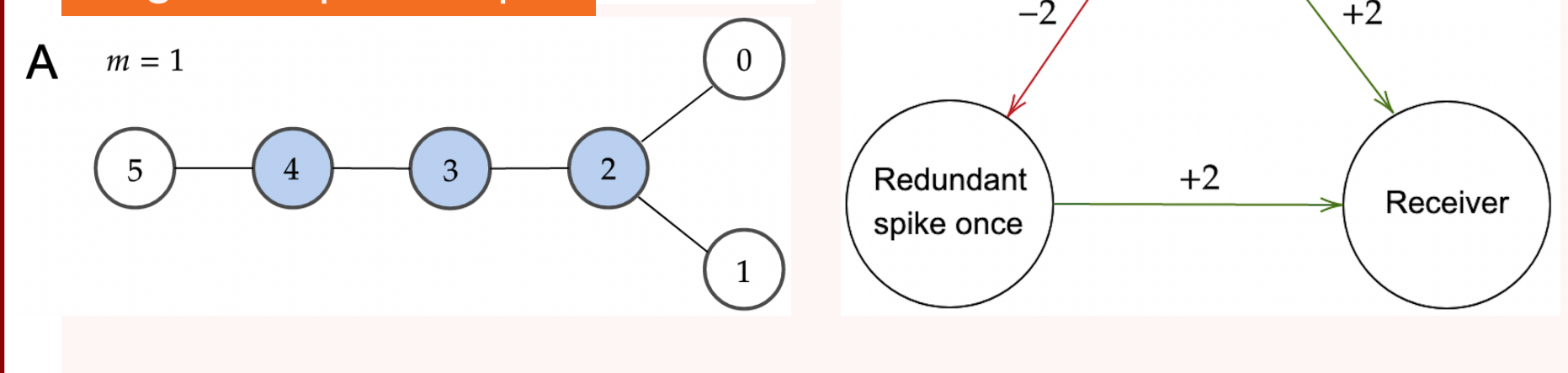
end

– The marked vertices are considered as the vertices in our total dominating set for G .

Next, an SNN implementation of this algorithm is generated using Leaky-Integrate-and-Fire (LIF) neurons. This implementation takes as input connected, triangle-free, planar graphs (E.g. Fig 1.).

Fig. 3: Redundancy

Fig. 1: Input Graph



Then it converts these graphs into the specification of an SNN that is encoded in a new graph (E.g. Fig 2.). These graphs can then be simulated using the Lava backend by Loihi, or a custom networkx SSN simulator backend.

This SSN implementation of the MDS approximation algorithm is

onwards referred to as the default network. This default network is enhanced with strategically placed redundant neurons that are inhibited by the default network neurons. Next, space radiation damage is simulated on the Loihi 2 in the form of random neuron deaths. These neuron deaths imply that a neuron is removed from the SNN, which can occur in both the default network and the set of redundancy neurons. If a default network neuron dies, the inhibition to the redundant neuron should be removed, causing the SNN to use the alternative neural pathway to recover from this damage. This usage of the alternative neural pathway simulates the multi-pathway structures found in brains of higher vertebrates and is proposed as the main adaptive mechanism in response to damage.

Fig. 2: Example SNN

