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

Akke Toeter[1,2] J.H.P. Kwisthout[1] D.M.Stam[2] A. Menicucci[2]

1 Radboud University, Nijmegen, Netherlands 2 Delft University, Delft, Netherlands

Radboud University

IN DEI NOMINE FELICITER

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

1 Select Distributed Algorithm

The Minimum Dominating Set Approximation algorithm as presented by Alipour et al., is specified as:

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

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

1. *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.*
2. *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**

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

   (b) *Unmark the marked vertices.*

   (c) *Each vertex marks the vertex with maximum w_i among its neighbour vertices.*

   end
3. *The marked vertices are considered as the vertices in our total dominating set for G.*

Fig. 1: Input Graph

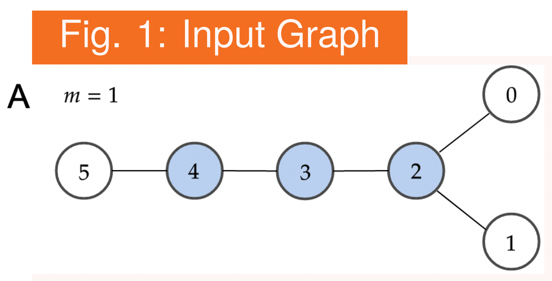
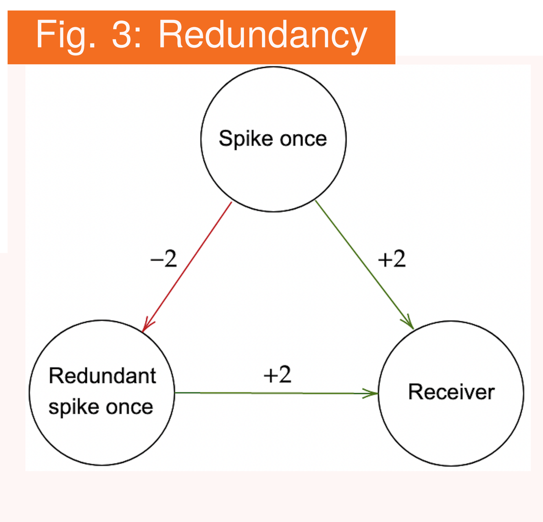
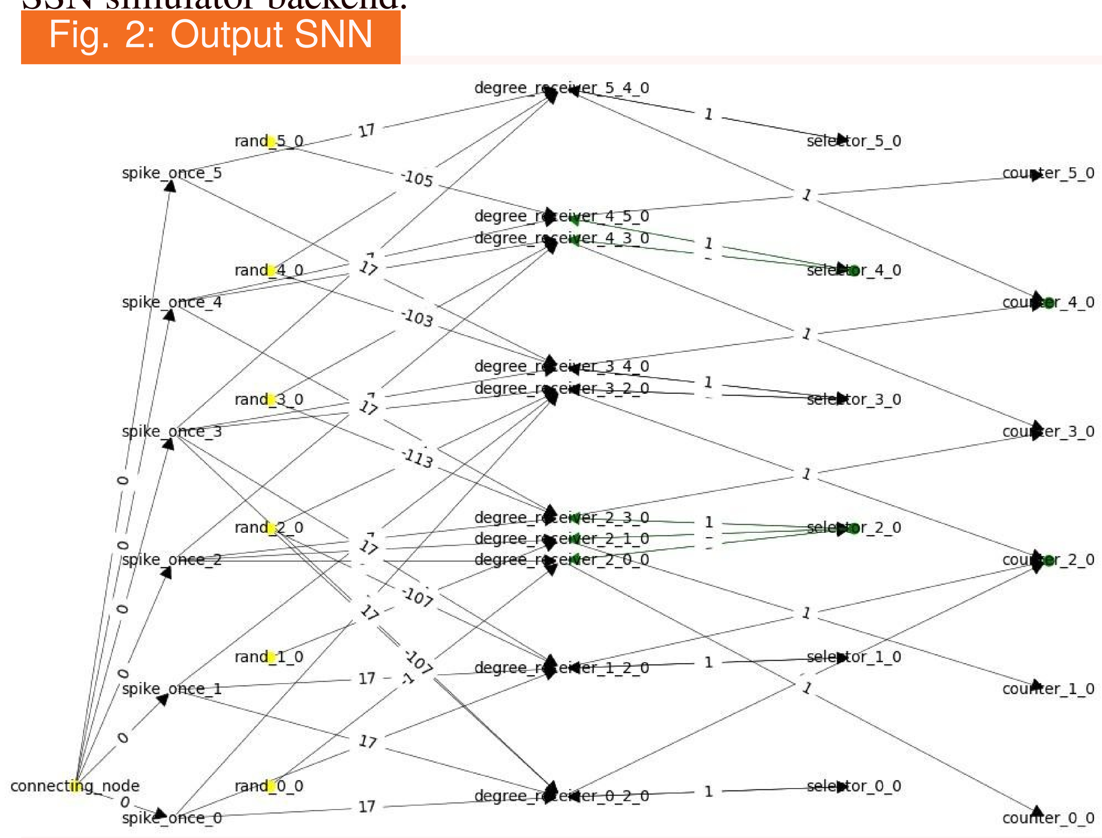


Fig. 3: Redundancy



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.

Fig. 2: Output SNN



2 Convert Algorithm to Spiking Neural Network(SNN)

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.).

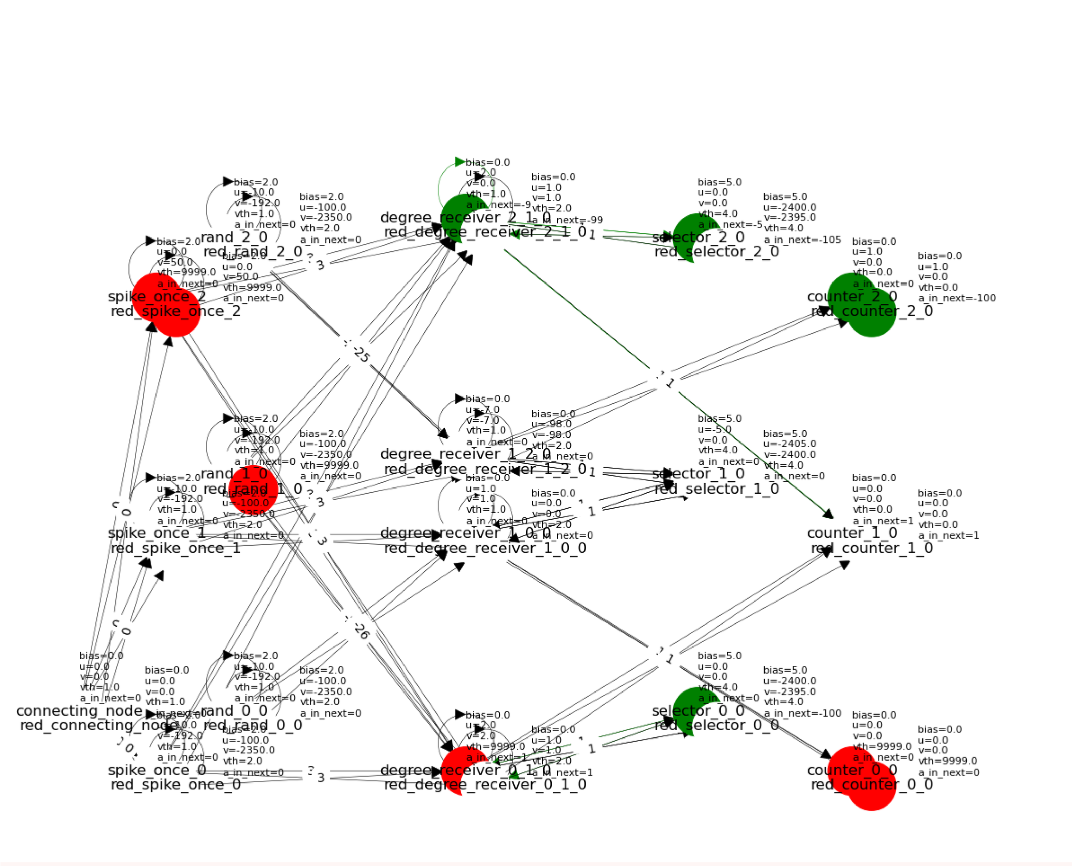
3 Apply Adaptation Mechanism to SNN

This default network is enhanced with strategically placed redundant neurons that are inhibited by the default network neurons.

4 Simulate Radiation on SNN

Next, space radiation damage is simulated in the form of random neuron deaths. Redundant neurons can die too.

Fig. 4: Adaptation: Redundancy (And Radiation in Red)



5 Compare SNN Performance With-/out Adaptation

Algorithm performance is compared with/without the adaptation mechanism when exposed to radiation.

RESULTS & DISCUSSION

Radiation Robustness

Table 1: Average fraction of correct outputs of the SNN implementation with and without adaptation. Neuron deaths can occur in default and redundant LIF neurons.

	Neuron Death Percentage in SNN			
Adaptation	0%	5%	10%	25%
Without	1		1	0
With	1		1	0.5

Neuronal, Synaptic & Energy Costs

Table 2: The multiple of the amount of neurons and synapses used by adaptation implementation, compared to the default SNN implementation.

	Average Cost of Adaptation Mechanism		
Graph Size	Neuronal	Synaptic	Spikes
3	5.7	8.3	32
4	5.8	10	37.5
5	5.8	10.2	64

Note this is the average overcapacity for $m = 0$ and $m = 1$ combined.

6 Discussion

The reliability of the results can be improved by running the algorithm on more and larger graphs. Running on the Loihi 2 using the Lava 0.4.0 Framework may facilitate this.

Population Coding

Other encoding mechanisms than sparse coding may be considered to realise radiation robustness. For example, in population coding, a population of neurons could be used to represent integer values instead of a single neuron.

Rate Coding

The first round of the algorithm by Alipour et al. has also been implemented using Lava V0.3.0 using a rate-coding approach, where the numbers are represented as a frequency. No radiation damage simulation has yet been performed on this implementation. However, it is expected that spike frequency modulation can be leveraged to mitigate radiation induced spike loss.

CONCLUSION & RECOMMENDATIONS

Brain-inspired adaptation mechanisms may be used in SNN implementations of graph optimisation problems to increase the radiation robustness of neuromorphic space hardware if SEE propagations can lead to neuron death. Creating more intelligent adaptation mechanisms than separate redundant neuronal pathways for each neuron may increase the radiation robustness of graph optimisation applications in space at a lower neuronal and synaptic cost.

7 Future Work

The overarching research project aims to perform physical radiation tests to gain more insight in the practical usefulness of brain-inspired adaptation mechanisms to hedge against radiation damage in neuromorphic space hardware. Since these tests are costly, a more thorough analysis on a broader scope of adaptation mechanisms is proposed. In particular, the population coding and rate coding options will be explored.

e-mail: akke.toeter@radboud.student.nl

FAST TU Delft University Fund

Presented at the ICONS in Knoxville, Tennessee (USA); on Thursday 28th July 2022