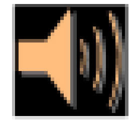
Leveraging brain-adaptation principles to increase radiation resistance of neuromorphic space hardware 

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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.

CCS CONCEPTS

• **Hardware → Circuit hardening**; *Transient errors and upsets.*

KEYWORDS

neuromorphic engineering, spiking neural networks, brain adaptation, radiation hardening

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1 BRAIN ADAPTATION

Four methods of brain adaptation have been explored within this research to find potential brain-inspired adaptation mechanisms for neuromorphic space hardware; redundancy, reorganisation, niche construction and timing of developmental trajectories. Starting with redundancy, it is noted that the brains of higher vertebrates often have multiple neural pathways that can support certain behaviour [**?**]. Using multiple pathways is considered a viable strategy of implementing brain adaptation in the generated SNN. However, for completeness, reorganisation and niche construction are also evaluated. Continuing with reorganisation, evidence suggests that the human brain becomes increasingly hierarchical during post-natal development [**?**]. No levels of hierarchy are found in the SNNs generated in for the MDS approximation. It is noted that for more advanced applications, such as on-site learning and retraining, the increases in hierarchy of the SNN might allow for automatic recovery after radiation exposure. An example could be a pre-trained network performing re-training after passing through the Van Allen belts before arriving at another solar body. Next, niche construction has been seen in some organisms that can change the neural pathways to select environment information based on a combination of which information the organism needs and what the brain can best process [**?**]. It is expected that including the aspect of what the brain can process best requires a highly advanced combination of objective functions and information input streams. This option is not considered feasible within this research project. Timing of developmental trajectories can be seen as a compensation mechanism that delays the development of certain brain regions such that the brain can sample information from early environments so that it can optimise its developmental structure [**?**]. The timing of developmental trajectories could be applied to a Mars rover that learns object detection on Mars instead of on Earth, using two different sensory inputs to provide input data and labels. If there are significant learnable differences with respect to the Earth environment, it could lead to a better trained model. In the context of the radiation robustness, the optimisation of the development structure could be used to ignore damaged neurons after radiation exposure. Redundancy is selected as the primary method of brain-adaptation for the selected SNN implementation of the algorithm because it does not require structural hierarchies nor model training.

To see how this redundancy can be implemented, the following neural coding mechanisms are evaluated:

- *Rate/frequency coding* - Assumes frequency or rate of action potential increases are accompanied by stimulus intensity increases.
- *Temporal coding* - Uses high-frequency firing rate fluctuations to convey information.
- *Population coding* - Represents stimuli using combined activities of multiple neurons.
- *Sparse coding* - Uses small subsets of neurons to encode items.

Rate/frequency adjustments can be used to increase or lower the *precision* of the spiking representation of numbers. By increasing the frequency, the relative impact of radiation induced spike omission could be reduced. Similarly, with population coding, the population size adjustments can be used to lower the relative impact of radiation induced neuron deaths on numerical representation accuracies. No useful implementations for temporal coding and sparse coding are found in the context of radiation robustness of the generated SNN algorithm for the MDS approximation.

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In order to increase the energy efficiency of the designed SNN implementation, a sparse coding scheme has been used. Single neurons and spikes are used to encode integers.

2 METHODOLOGY

The research methodology starts in section 2.1 with a description of the minimum dominating set (MDS) approximation algorithm by Alipour, the SNN implementation of this algorithm by Diehl et al., and the implemented form of brain adaptation [?][?]. Since the overarching research project aims at performing physical radiation tests, section 2.2 specifies the hardware that is used for testing, and how the radiation effects are simulated. The test procedure is detailed in section 2.3.

2.1 Algorithm Selection

The MDS approximation as presented by Alipour et al., is specified in Alg. 1. Next, an SNN implementation of this algorithm is

Algorithm 1: Distributed Algorithm for computing a total dominating set in a graph with given integer $m \geq 0$.

Input: Connected, planar, triangle-free graph of size n.
Output: Set of nodes that form a minimum total dominating set (MDTS).

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
8: The marked vertices are considered as the vertices in our total dominating set for G.;

generated using Leaky-Integrate-and-Fire (LIF) neurons. This implementation is created by Diehl et al. [?] using the open-source Lava software framework by Intel. This implementation takes as input connected, triangle-free, planar graphs (E.g. fig. 1). Then it converts these graphs into the specification of an SNN that is encoded in a new graph (E.g. fig. 2). A recursive method then takes a single neuron and converts the encoded SNN that is encoded in the graph into an actual functional SNN that can be run on the simulated on a regular computer.

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

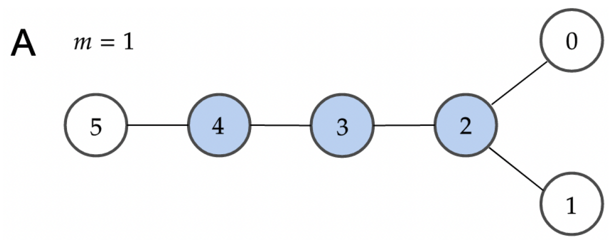

Figure 1: Example input graph. For $m = 1$ the algorithm still selects 3 nodes as it is an approximation of the MDS.

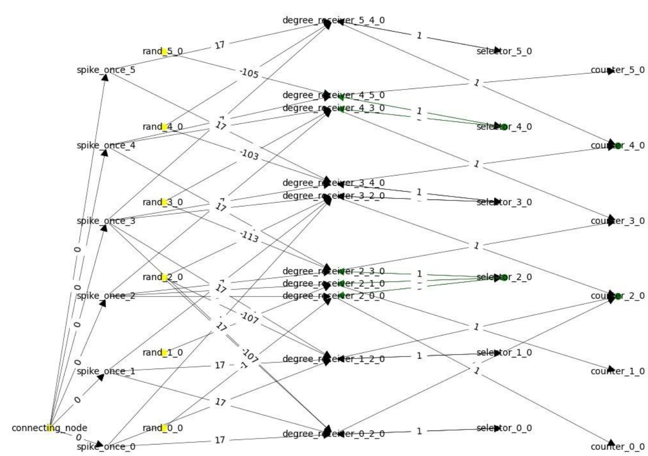

Figure 2: Example SNN encoding of algorithm to approximate MDS on the input graph of fig. 1. This module is connected in series where the mark counter neuron takes up the role of spike_once neuron in the next round of the approximation algorithm. For a more detailed description of the SNN implementation the reader is referred to Diehl et al. [?].

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.

2.2 Hardware

At the time of writing, no single-event effect (SEEs) propagation mechanisms are identified for space radiation exposure on the Loihi 1 & 2 neuromorphic chips, a high-level software simulation of these single-event effects is performed. This is done by assuming that the non-neuromorphic components of the chips are performing nominally, and that the SEEs propagate from, for example, transient bit-flips, towards neuronal and synaptic parameter changes. The first assumptions may be accurate if local radiation hardening and redundancy is applied to the non-neuromorphic components. Weight and/or energy saving could be a motivation to apply these radiation counter-measures sparsely. The second assumption is based on the digital nature of the components that make up the neural components of the Loihi. The components that make up the neural compartments and synapses of the Loihi are visualised in fig. 3.

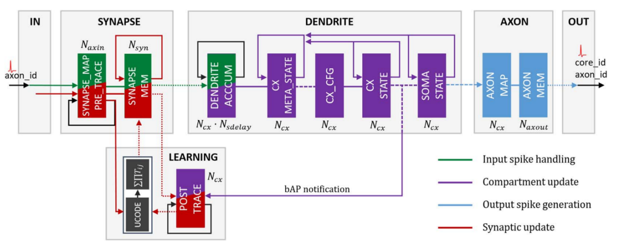

Figure 3: Core Top-Level Microarchitecture of the Loihi chip. The SYNAPSE unit processes all incoming spikes and reads out the associated synaptic weights from the SRAM memory [?] .

2.3 Testing

To test whether the brain adaptation implementation may be used to increase radiation robustness of neuromorphic space hardware, it is compared to a baseline without brain adaptation.

2.3.1 Metrics. The metrics of the comparison are:

(1) *Radiation Robustness* - a percentage score indicating the ratio of successful solution generation on random input graphs.
(2) *Neuronal & Synaptic Overcapacity* - a factor from 0 to n, indicating the ratio of redundant neurons and synapses with respect to the original implementation without adaptation implementation.
(3) *Energy Efficiency* - the number of spikes consumed by implementations.

2.3.2 Simulated Radiation Damage. This work simulates radiation damage propagation of SEEs as neuron deaths by setting the neuron thresholds $vth = 1000[V]$ at from the start of the simulation. The 1000 [V] is arbitrary yet large enough to prevent spiking. Transient effects are ignored along with neuron property changes in $\delta u, \delta v, bias$, synaptic death, and synaptic property changes in: $sign, weight$.

2.3.3 Brain Adaptation Mechanism. The selected SNN implementation is enhanced with redundant neurons and neuronal pathways to realise simulated radiation robustness. A basic example is shown in fig. 4.

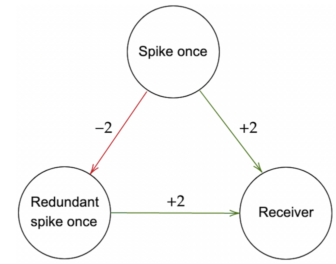

Figure 4: Alternative neural pathway for a redundancy of the spike_once neuron. If the spike_once neuron dies due to simulated radiation-induced SEEs ($vth = inf$), the redundancy neuron inhibition is eliminated. Without inhibition, the redundant spike_once neuron copies the spike_once behaviour with a delay of 1 timestep.

The alternative neural pathway renders a single neuron $original_i$ with a input synapses, and b output synapses, redundant at the cost of $2a + 2b$ synapses and 2 neurons. This cost can be reduced by implementing a controller that scans the network and manually redirects neural pathways to a smaller buffer network. However, that shifts the radiation robustness problem as that controller may also endure SEEs. One can also add triple/n-factor redundancy by including more redundant spike_once neurons that are inhibited by the original spike_once neuron and each other. This induces an additional delay of t=1 time step per redundant neuron.

3 RESULTS

3.1 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

3.2 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.

4 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.

The apparent non-linear growth of the energy consumption in terms of spikes is not expected for the brain adaptation implementation. This is not expected because the redundant neurons should either be inhibited once, or, if they take over from the dead neuron, repeat the exact same spike pattern the dead neuron would have given. This would result in an additive spike increase of roughly the SNN size, not in an exponentially growing multiple. After inspecting the spike behaviour, it is noted that some of the inhibition between neurons and redundant neurons does not stop over time. This causes unneeded spikes generation.

Even though no public SEE propagation mechanisms are known for the Loihi 2 at the time of writing, the representativeness of the simulation can be increased by taking transient effects, synaptic changes, neuron property changes and Von Neumann component malfunctions into account. The current form of redundancy that is implemented is still dependent on particular neuron properties, and no automated method for arbitrary LIF neuron redundancy is presented. A more intelligent adaptation mechanism may allow for a more active neural pathway redirection to realise equivalent robustness levels at a lower neuronal and synaptic overhead.

4.1 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. The `spike_once` neuron with a synaptic output weight of x could be replaced by x neurons along with m excitatory controller neurons that verify whether each of those neurons is still functional. If part of the population dies, the controller neurons can excite parts of the population to compensate this loss. The m controller neurons could inhibit each other and form a redundancy in the redundancy mechanism.

4.2 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.

4.3 Algorithm Selection

This work has focussed on a particular optimisation problem, it can be noted that clever algorithm selection (and/or design) for radiation robust SNNs may be used to exchange approximation accuracy for robustness. For example, instead of selecting an algorithm that breaks if a single neuron dies, one could consider shortest-path algorithms that automatically yield a longer path that works around the neuron death. Furthermore, selecting applications that are closer to natural brain functionalities, such as event-based vision, may facilitate brain adaptation mechanisms at a lower cost. For example, in some deep neural networks, neuron death may be a feature instead of a bug, as the retraining phase can in some cases be used to increase the generalisability of the network.

4.4 Physical Testing

Many of the discussed brain adaptation implementations will fail if the boiler-plate architecture of the SNN suffer from SEEs. This issue can be resolved using fault-tolerance acceptance, redundancy and/or local shielding of boiler-plate architecture components, and by taking boiler-plate SEE propagation mechanisms into account in SNN design. The latter would require physical testing and/or detailed hardware analysis. Industry partners of the Intel Neuromorphic Research Community, such as ESA, NASA and Raytheon are also working on radiation robustness [**?**] and may be able to share insight in the more detailed radiation effects on the Loihi 2 without incurring export license limitations.

5 CONCLUSION

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.

6 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, and the focus is shifted to more AI oriented applications. section 4.3 to section 4.4.

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