Neuromorphic Computing for Spacecraft's Terrain Relative Navigation: A Case of Event-Based Crater Classification Task

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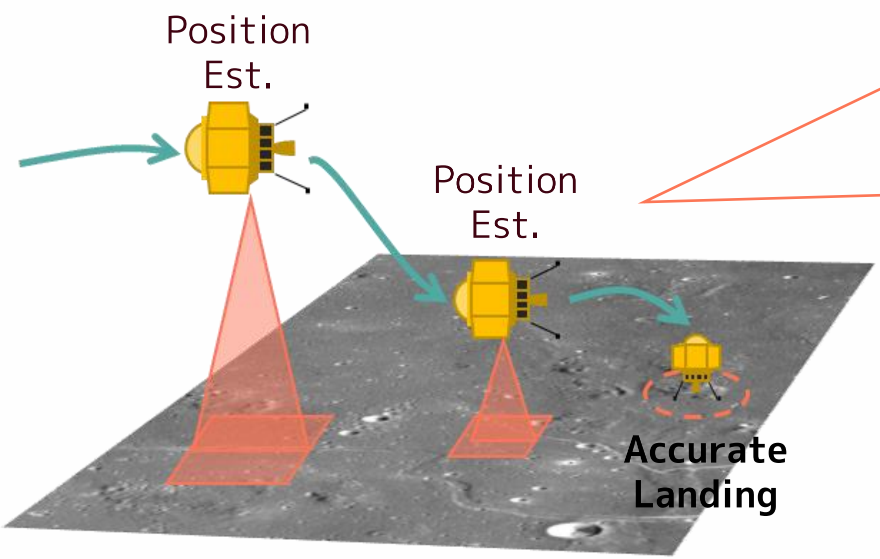
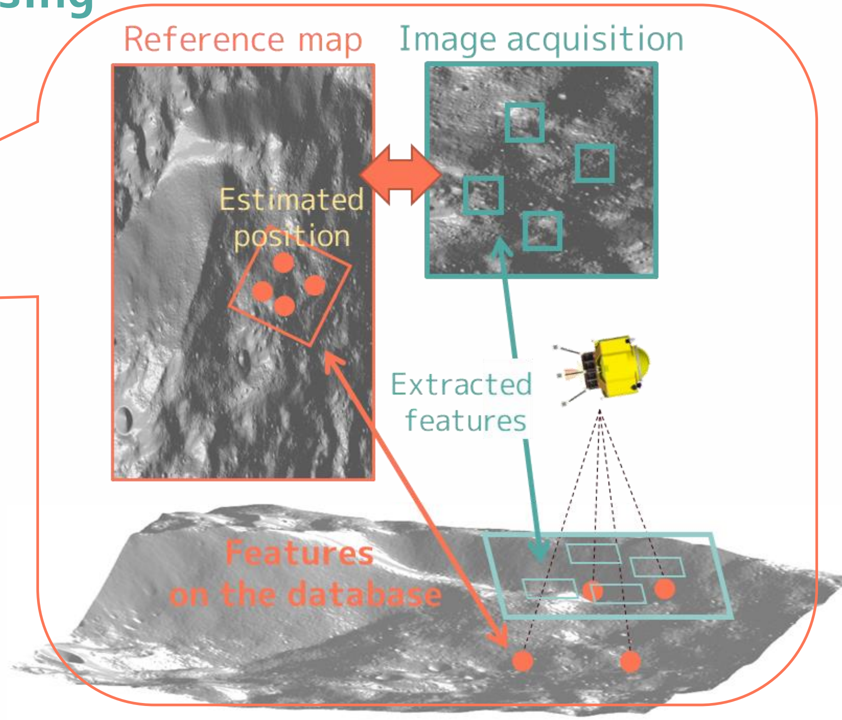
The 8th Annual Neuro-Inspired Computational Elements (NICE) workshop

Advancement of Landing Exploration Missions

- **Image processing for accurate landing of robotic spacecraft**
  - Estimation of position and/or velocity autonomously
  - **Feature extraction and matching tasks** in terrain images
- **Needs of real-time autonomous processing**
  - High-velocity decent, communication delay
  - **On-board and real-time processing**



Navigation by Image Processing



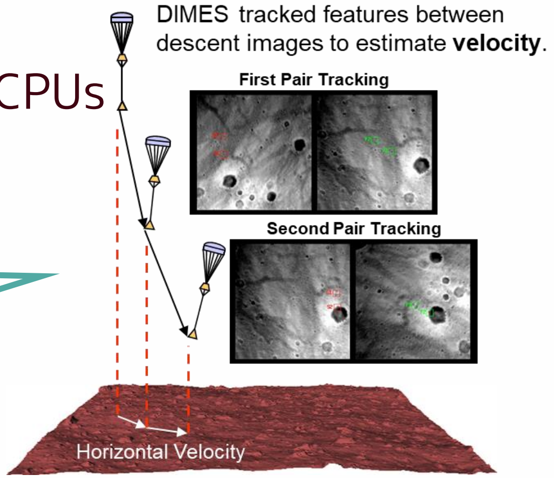
Terrain Relative Navigation

Computing Environment in Spacecraft

Difference between spacecraft and ground

- Performance: **~1/100** lower than general purpose CPUs
  - **Thermal constraints** and radiation tolerance

e.g.) Image processing on the Mars lander
- Feature tracking between image frames
- Processing of three frames totaling about 14 seconds on a PowerPC-based CPU



An example of image processing on the Mars lander[1)]

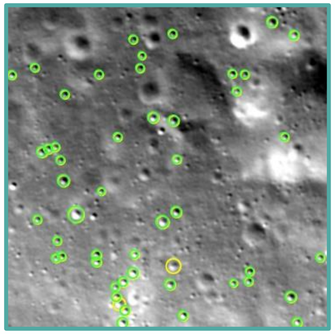
To perform vision-based navigation with low-power consumption is required

CPU/FPGA-based processors for commercial and space[2)]

Device	Max. Frequency	DMIPS/Logic	Power
Intel Core i7-8700	3.20 GHz	30,000	65 W
RT RAD750	~200 MHz	260	14 W
AT697E SPARC V8	100 MHz	86	1 W
Xilinx Zynq-7100	1 GHz	444,000 LC	20 W
Xilinx Virtex-5QV	205 MHz	81,920 LUT6	5-10 W
Microsemi RTG4	300 MHz	151,824 LE	1-4 W

1) Johnson, A., et al., IJCV, 74.3, pp. 319-341, 2007. 2) Lentaris, G., et al., AIAA JAIS, 15.4, pp. 178-192, 2018.

Expectations for Neuro-inspired Computing



- **Functions to be performed on-board**
  - Landmark recognition for terrain feature extraction
    - Craters, rocks, surface textures, etc.
  - Feature matching/tracking for pos/vel estimation
- Real-time execution is difficult even for traditional algorithms

Neuro-inspired computer

- Operates at low speed (< KHz)
- Asynchronous (clock free)
- Integrated memory & computation
- **Power and energy efficient**
- Works as **neural network**

Conventional computer

- Operates at high speed (> GHz)
- Synchronous (global clock)
- Memory & computation are separated
- **Power and energy hungry**
- Works using logic gates

Is NC useful for vision-based navigation tasks?
(in terms of power consumption)

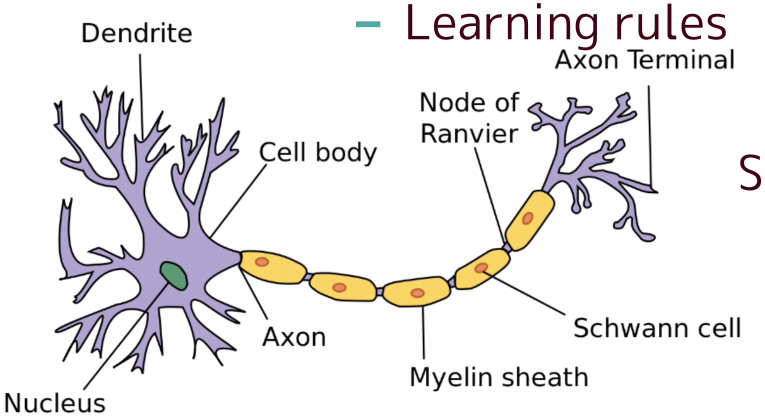
Challenges of Neuro-inspired Computing in-Space

- Processors are in the R&D phase[3)]
  - Radiation tolerance/vacuum environment?
- **No specific space applications exist**
  - This study addresses it

Difficulties in neuromorphic apps developing

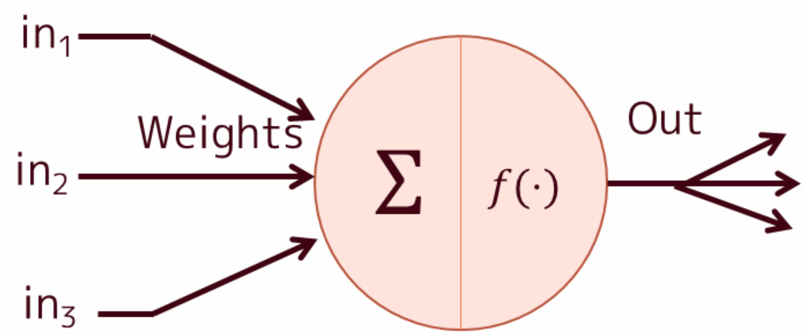
- Neuro-inspired processors work as **Spiking Neural Network (SNN)**
  = Can not work as well as Artificial Neural Network (ANN)
  - Data input method
  - Computing method
  - Learning rules

  } Differences between them



Biological (spiking) neuron

Simple model



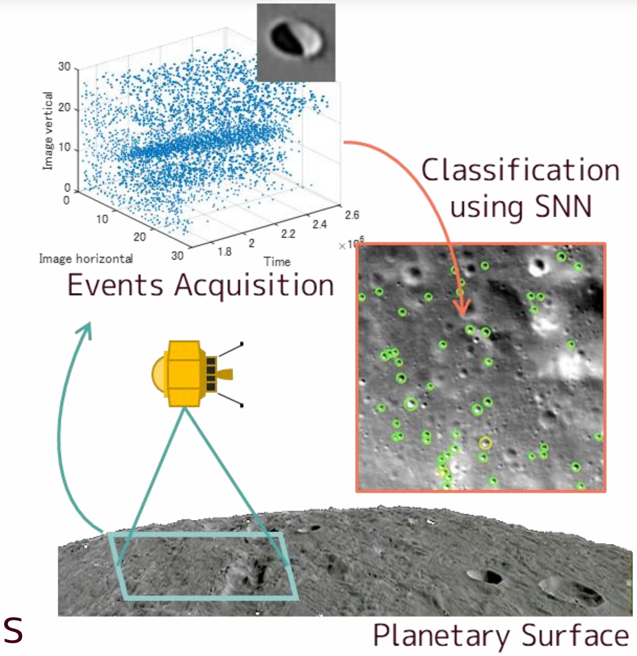
Artificial neuron

3) Bersuker, G., Mason, M., and Jones, K. L.: Neuromorphic Computing: The Potential for High-Performance Processing in Space, 2018

Conversion Method

Target task and approach

- Crater classification for landmark extraction
  - Sensor; event-based camera
- Using ANN converted with rate coding
  - Want to compare performance with existing ANNs
  - The LIF response curve is used Hunsberger & Eliasmith (2015)



Learning methods of SNNs

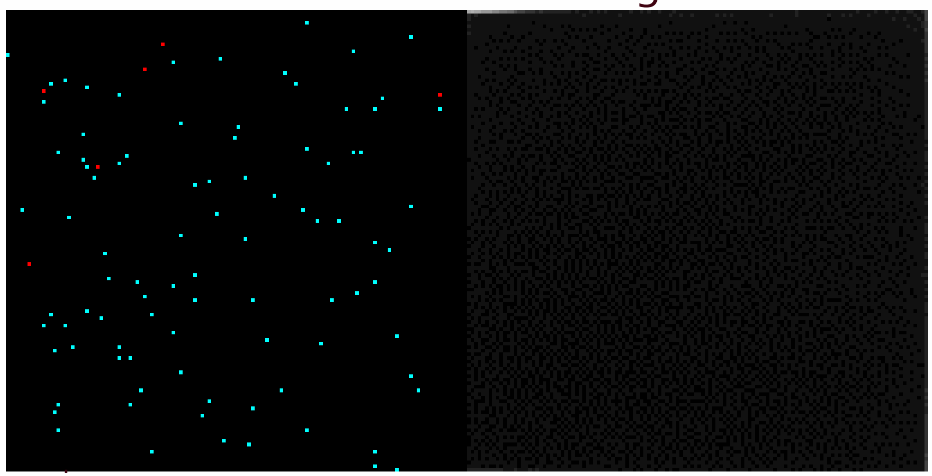
	Pros	Cons
ANNs converted w/ rate coding	**Directly utilize ANN applications**	Poor scaling
Off-line backprop trained	Non-numeric data can be trained	Hard to train
Online backprop trained	Well suited for SNN (continuous adaptation)	Hard to train

Crater Event Dataset

Generating a crater event dataset

- Create a movie that moves original images in one direction (left) at 3 pix/s.
- Create a dataset by capturing video on a monitor with DAVIS346
- ANN input is calculated firing rate of the event data

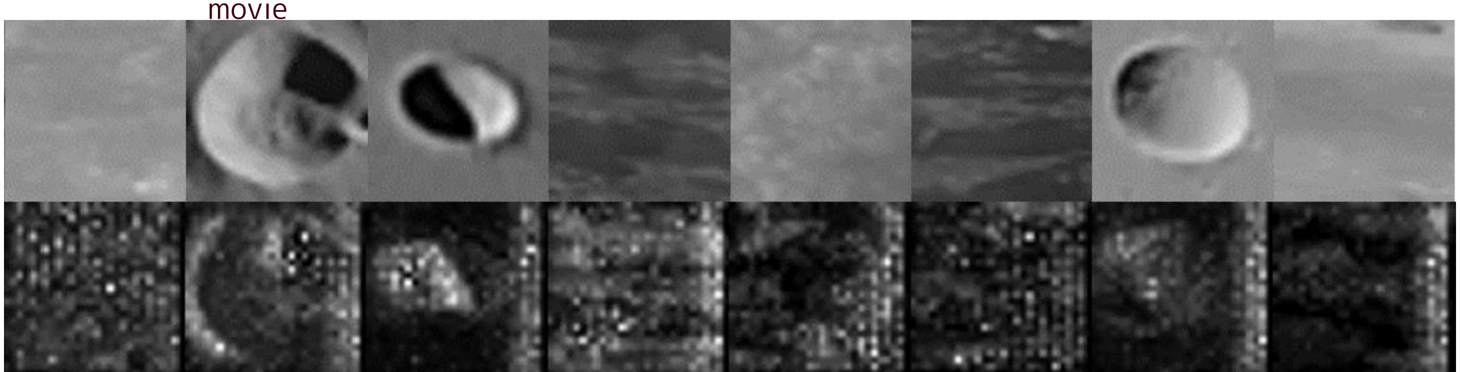
Event data Original movie



movie

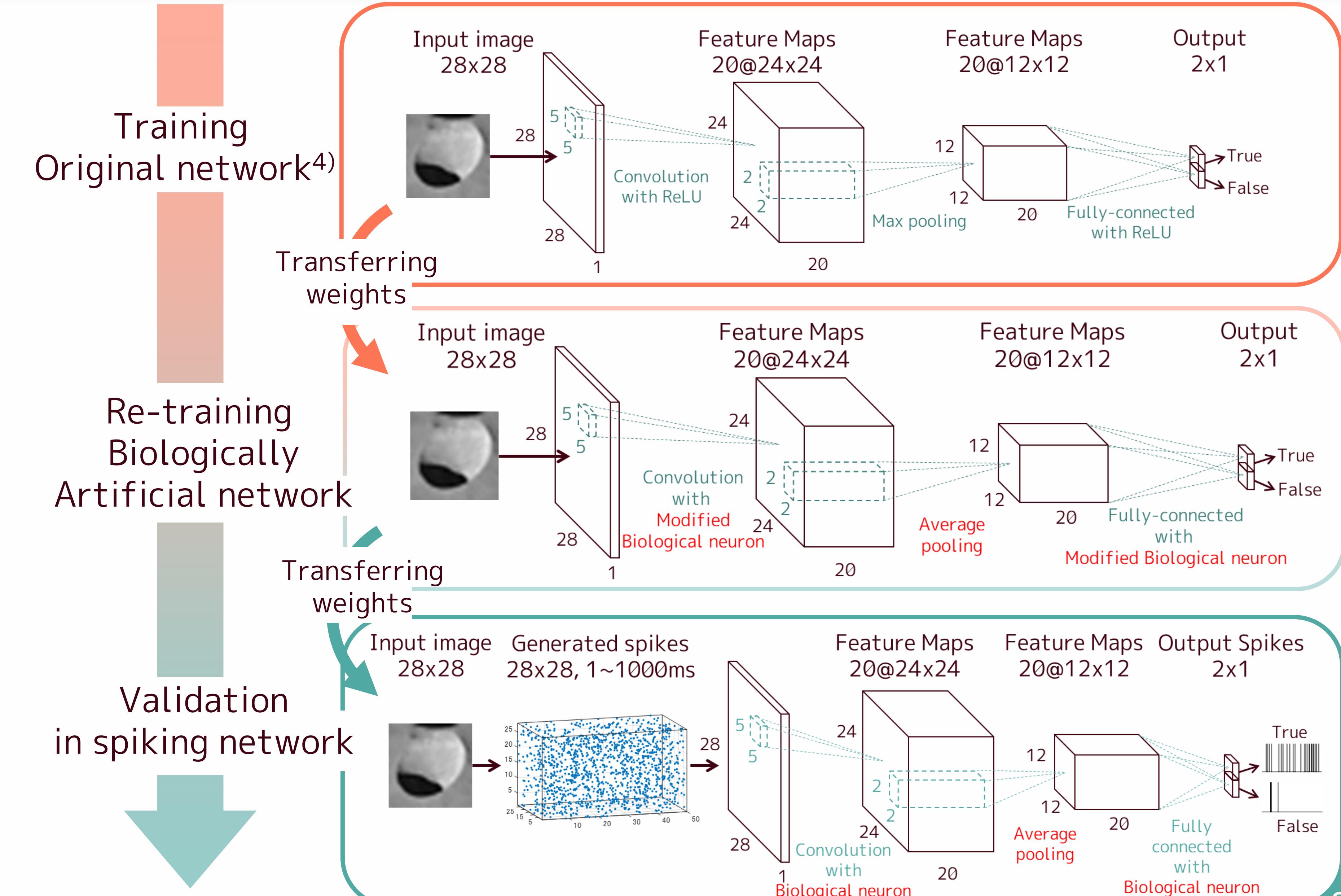
Original image

Firing rate



Conversion Method and Target Task (Crater classification)

4) Ishida, T., Takahashi M., Fukuda, S., 32nd ISTS, 2019



Simulation Results

Classification accuracy in each step

	Accuracy
Step1(ANN)	94.7%
Step2(BANN)	91.2%
Step3(SNN)	**90.2%**

- **Classification accuracy**
  - Accuracy decrease of about 4.5% from original ANN
- **Energy analysis**
  - Several developed processors show energy consumption $\boldsymbol{\alpha}$
  - Total spike: 230×10^6

$$\text{Total power consumption [W]} = \text{total spikes} \times 1\ \text{[image/s]} \times \alpha\ \text{[pJ/spike]}$$

$$= 230 \times 10^6 \alpha\ [\mu\text{W}]$$

Estimates of SNN power consumption

Neuromorphic processors	Event-cam dataset
Merolla, et al.[5] ($\alpha = 45$)	**900 μW**
Cruz-Albrecht, et al.[6] ($\alpha = 0.37$)	**7.40 μW**

5) Merolla, P., et al., Science, 345.6197, pp. 668-673, 2014
6) Cruz-Albrecht, J. M., et al., IEEE Transactions on Biomedical Circuits and Systems, 6.3, pp. 246–256, 2012.

For future works

Summary

- On-board image processing technology is important in the advance of landing navigation technology of spacecraft.
- Space-grade computers have much lower performance than their commercial counterparts, and power consumption is the main cause of their lower performance.
- Neuro-inspired computers have potential to meet this issue and can perform advanced image processing tasks.
- In this study, we performed a simple task using an event camera as input, and confirmed that low power consumption can be expected.
- We will continue to study specific hardware and software suitable for landing navigation technology.

Future work

- Evaluate in detail using actual neuromorphic processors
  - Processing speed
  - Radiation tolerance
- Develop more specific navigation applications
  - Applications that match the characteristics of the event camera and SNN