Neural-Network-Based Event Reconstruction for the RadMap Telescope

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11 Oct 2023 | 8th Connecting the Dots Workshop, Toulouse
The Space Radiation Environment

Composition and Sources

1. Galactic cosmic rays (GCR): 2% electrons, 98% protons and high-energy heavy ions
2. Solar energetic particles (SEP) and solar wind: protons, electrons, and alpha particles
3. Van-Allen Radiation belts, SAA: protons and electrons
4. Secondary radiation: mix of charged particles and neutrons

Objective: Assess shielding requirements and their temporal variations to minimize exposure to damaging radiation on future (manned) missions
Overview

1. The RadMap Telescope
2. Training Data
3. Event Reconstruction
   3.1 Particle-Track Reconstruction
   3.2 Particle Identification
   3.3 Energy Reconstruction
The RadMap Telescope

Capabilities

**ADU | Precise Tracking & Particle Identification**

Energy Range: \( > \sim 70 \text{ MeV/n} \)
Energy Resolution:
- 1% for \(<90 \text{ MeV (protons)}\)
- 7% for \(<200 \text{ MeV (protons)}\)
Angular Resolution: \(< 2^\circ\)
Coverage: Full solid angle
Geom. Acceptance:
- 1013 cm\(^2\)sr (detection)
- 925 cm\(^2\)sr (reconstruction)

**M-42 | Dosimetry**

Energy Deposition Range: 60 keV to 17.7 MeV
Resolution: 1004 channels, 17.6 keV width
Coverage: Full solid angle

**Advantages**

- Single, general-purpose radiation monitor
- Monitoring of particle-type resolved, biologically meaningful dose rates on the ISS (and beyond)
- Omnidirectional sensitivity & tracking over full solid angle
- Designed for identification of particle species in critical energy region (\(~ \text{hundreds of MeV/n}\) )
- Goal: analysis on-orbit and in near-real time
The RadMap Telescope

ADU Detector Concept

- Active tracking volume of ≈ 8 x 8 x 8 cm³

- 1024 scintillating-plastic fibres
  - Organised in 32 layers of 32 fibres each
  - Fibres of one layer rotated by 90 deg in-plane compared to the fibres of the neighboring layers
  - Omnidirectional acceptance

- Four identical, vertically stacked modules

- Custom SiPM arrays

- Two two-dimensional projections of energy depositions
Reconstruction of tracks from spatial distribution of energy depositions

Reconstruction of charged-particle characteristics using Bragg Curve Spectroscopy
  - Unique energy-loss profiles of low-energy ions along their track
  - Shape of the profiles depending on the particles’ velocity, charge and mass

In principle most reliable for stopped particles
  - But extension of the measurement range by extrapolation of the Bragg curve for through-going particles

Decreasing separation power for increasing energy deposition / particle charge due to ionization quenching
Training Data

Simulation and Composition

- Training data simulated with Geant4
- Distributions modeled to cosmic ray abundances but adapted to optimize training of neural networks
Training Data
Simulation and Composition

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- Particle types
  - Fully-ionized, most-common isotopes of elements from hydrogen to iron as they appear in cosmic rays
  - Uniform distribution of ion types
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- Angles of incidence
  - Isotropic distribution
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- Particle energies
  - 70 MeV to 50 TeV
  - Log-uniform energy distribution
Training Data
Simulation and Composition

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- Particle types
  - **Fully-ionized, most-common isotopes** of elements from hydrogen to iron as they appear in cosmic rays
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- Angles of incidence
  - **Isotropic distribution**

- Particle energies
  - 70 MeV to 50 TeV
  - **Log-uniform energy distribution**

- Minimum of **3 fiberhits** in each projection
Neural-Network-Based Event Reconstruction

Reconstruction Tasks

- Ground-based training of neural networks and subsequential deployment onto on-board computer to comply with computational restrictions to in-orbit analysis

- Two two-dimensional (16x32)-projections of the detector signal as input

- Separate neural-network framework for each of the three reconstruction tasks
Neural-Network-Based Event Reconstruction

Particle-Track Reconstruction – Parametrisation

• **Parametrisation** of three-dimensional track
  • $\vartheta \in [0, 180)$ deg
  • $\phi \in [-180, 180)$ deg
Neural-Network-Based Event Reconstruction

Particle-Track Reconstruction – Neural Network Architecture

- **Parametrisation** of three-dimensional track
  - $\theta \in [0, 180)$ deg
  - $\phi \in [-180, 180)$ deg

- Dual classification over 180 resp. 360 classes
  - $\Rightarrow$ Binning resolution of 1°

- **Inception layer** (arXiv:1409.4842)
  - Multiple convolutions of different size in parallel
  - Learns the scale of structures of interest

- Training parameters:
  - Nb. of trainable parameters: 2 793 840
  - 10M training events (7-2-1)
  - 400+ training epochs
Neural-Network-Based Event Reconstruction

Particle-Track Reconstruction – Results

\[ \sigma_\theta = 1.15 \text{ deg} \]

\[ \sigma_\phi = 1.02 \text{ deg} \]
Neural-Network-Based Event Reconstruction

Particle Identification – Network Architecture

• Identification of fully-ionized, most common isotopes of H to Fe

• Multiple Inception layers (arXiv:1409.4842)
  • Multiple convolutions of different size in parallel
  • Learns the scale of structures of interest

• Training parameters:
  • Nb. of trainable parameters: 2 110 474
  • 1M training events (7-2-1)
  • 30 & 100 training epochs
Neural-Network-Based Event Reconstruction

Particle Identification – Network Architecture

- Identification of fully ionized, most common isotopes of H to Fe

- Multiple Inception layers (arXiv:1409.4842)
  - Multiple convolutions of different size in parallel
  - Learns the scale of structures of interest

- Training parameters:
  - Nb. of trainable parameters: 2 110 474
  - 1M training events (7-2-1)
  - 30 & 100 training epochs

- Two-step classification:
  1) Identify lighter ions (H to F)
     Filter out heavier ions
  2) Apply additional NN to identify heavier ions
Particle Identification – Results

Accuracies

Overall: 51 %

Light ions:
- H 93 %
- He 90 %
- Li 79 %
- Be 79 %

Heavier ions:
- Si 35 %
- Ca 24 %
- Fe 26 %
Neural-Network-Based Event Reconstruction

Particle Identification – Results

Accuracies

Overall: 51 %

Light ions:
- H: 93 %
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- Fe: 26 %

Z±2:
- Overall: 86 %
- Light ions: 99 %
- Heavier ions: 83 %

Accuracy vs. Z

- Z+=0
- Z+=1
- Z+=2
Neural-Network-Based Event Reconstruction

Energy Reconstruction – Network Architecture

• Reconstruction of **energy per nucleon**

• **Energy range** of the particles: 50 MeV/n to 1 GeV/n

• Same network architecture as for particle identification
  – with some adapted parameters

• Training parameters:
  • Regression task: real-valued energy prediction
  • Nb. of trainable parameters: 2 109 313
  • 49 training epochs
Neural-Network-Based Event Reconstruction

Energy Reconstruction – Protons: MC-based Selection

- 10M training events
- MC-truth-based selection of protons and energy range $E < 1\text{GeV}$
Neural-Network-Based Event Reconstruction

Energy Reconstruction – Protons: NN-based Selection

• NN-based selection of protons and energy range $E < 1\text{GeV}$
Neural-Network-Based Event Reconstruction
Energy Reconstruction – All Ion Types H to Fe

• Simultaneous energy reconstruction for all ion types from H to Fe
• 1M training events

• Overlapping stopping ranges of the different ion types
• Additional processes involving heavier ions (e.g. fragmentation)

• Mostly through-going particles
• Less fluctuations
• Energy resolutions between 20 and 30%
SpaceX CRS-27
15 March 2023, 00:30 UTC
LC39A, Kennedy Space Center

Outlook and First Measurements
On-Orbit Operations
Deployment Locations

US Lab

Node 3

COL – Columbus Orbital Facility

JEM-PM – Japanese Experiment Module
Orbit Correlation of Count Rates

Aug 11 – Aug 27 & Aug 29 – Sep 5

Count rate (1/s)
First Measured Tracks

Some (Uncalibrated) Examples...
First Measured Tracks

Some (Uncalibrated) Examples…
Neural-Network-Based Event Reconstruction

Energy Reconstruction – Protons: NN-based Selection

![Graph showing predicted vs. true particle type and energy ranges.](image-url)
Neural-Network-Based Event Reconstruction

Energy Reconstruction – Protons: NN-based Selection
Count Rates

*ADU & M-42 in JEM*

- Average ADU rate: 250 1/s
- Max. rate up to ~6000 1/s

- Scaling of ADU and M-42 count rates with
  \[ GF_{ADU} = 1013 \text{ cm}^2\text{sr} \]
  \[ GF_{M-42} = 7.61 \text{ cm}^2\text{sr} \]