A Multi-Purpose Particle Detector for Space Missions

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CTD/WIT17

March 6, 2017

Radiation in Space

COGNITIVE NEUROSCIENCE

What happens to your brain on the way to Mars

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10.1126/scia

As NASA prepares for the first manned spaceflight to Mars, questions have surfaced concerning the potential for increased risks associated with exposure to the spectrum of highly energetic nuclei that comprise galactic cosmic rays. Animal models have revealed an unexpected sensitivity of mature neurons in the brain to charged particles found in space. Astronaut autonomy during long-term space travel is particularly critical as is the need to properly

Apollo Lunar Astronauts Show Higher Cardiovascular Disease Mortality: Possible Deep Space Radiation Effects on the Vascular Endothelium

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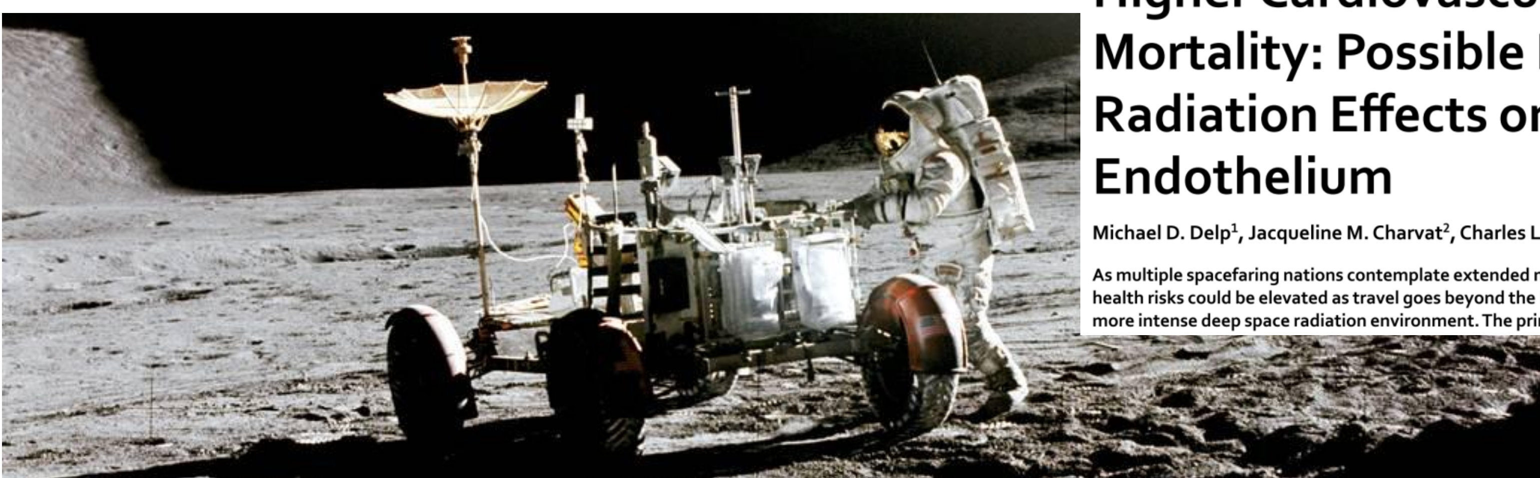
As multiple spacefaring nations contemplate extended manned missions to Mars and the Moon, health risks could be elevated as travel goes beyond the Earth's protective magnetosphere into the more intense deep space radiation environment. The primary purpose of this study was to determine



Types of Radiation

Galactic Cosmic Rays (GCR)

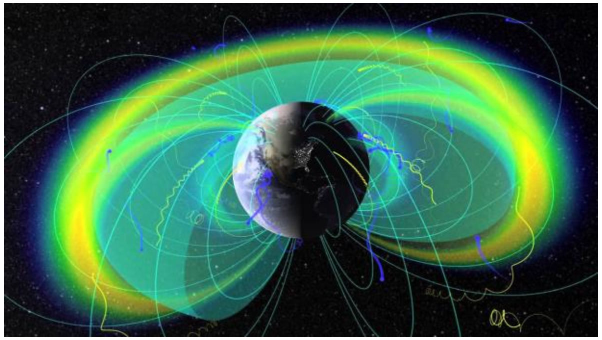
- 98% nuclear component
  - 87% protons, 12% helium, 1% heavier elements
- 2% electrons
- energies up to 10^{20} eV
- galactic sources: supernovae
- extragalactic sources for highest energies?
- hardly shieldable

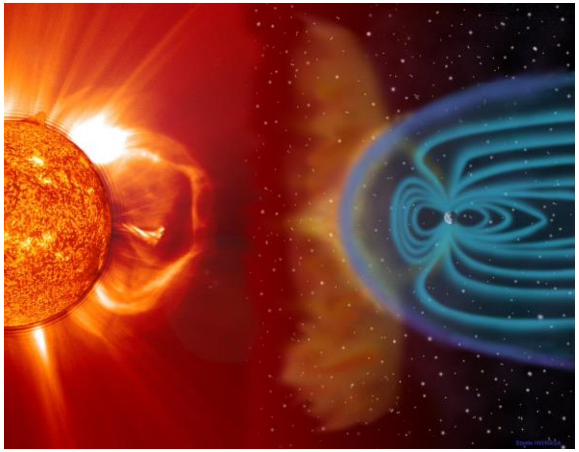
Solar Energetic Particles (SEP)

- protons, electrons, some nuclei
- energies up to several GeV
- travel along interplanetary magnetic field lines
- potentially harmful events quite rare
- strongly varying particle flux
- easily shieldable, except during EVA

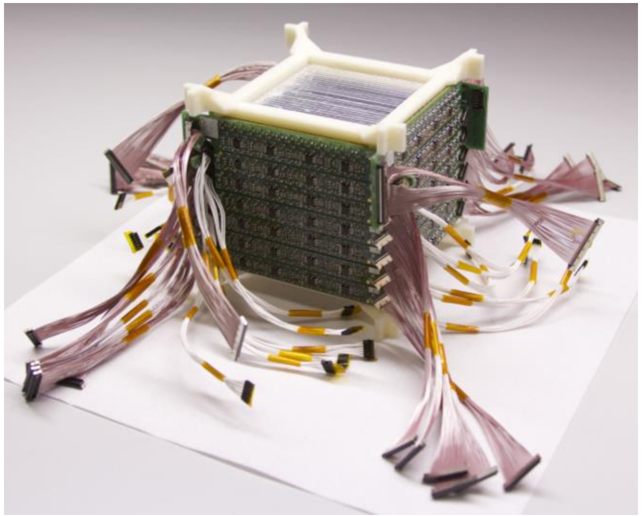
Van Allen Radiation Belts

- Earth's magnetic field
  - deflects low-energy particles (GCR & SEP)
  - traps particles
- energies up to
  - 7 MeV (electrons)
  - 2 GeV (protons)





The Multi-Purpose Active-Target Particle Telescope

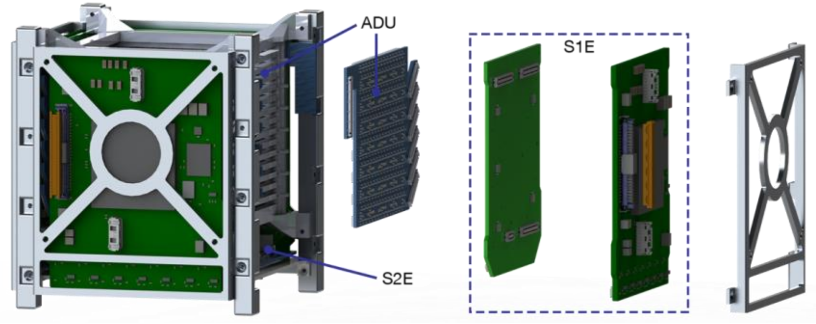


energy range: > 25 MeV/n
energy resolution: < 2% (25 to 100 MeV)
(protons) < 10% (100 to 600 MeV)
angular resolution: ~ 3°
geometrical acceptance: 800 cm²sr

full solid-angle coverage
tracking calorimeter
particle ID for low-energy charged particles

total mass: 3 kg
dimensions: 12 x 12 x 12 cm³
power consumption:~30 W

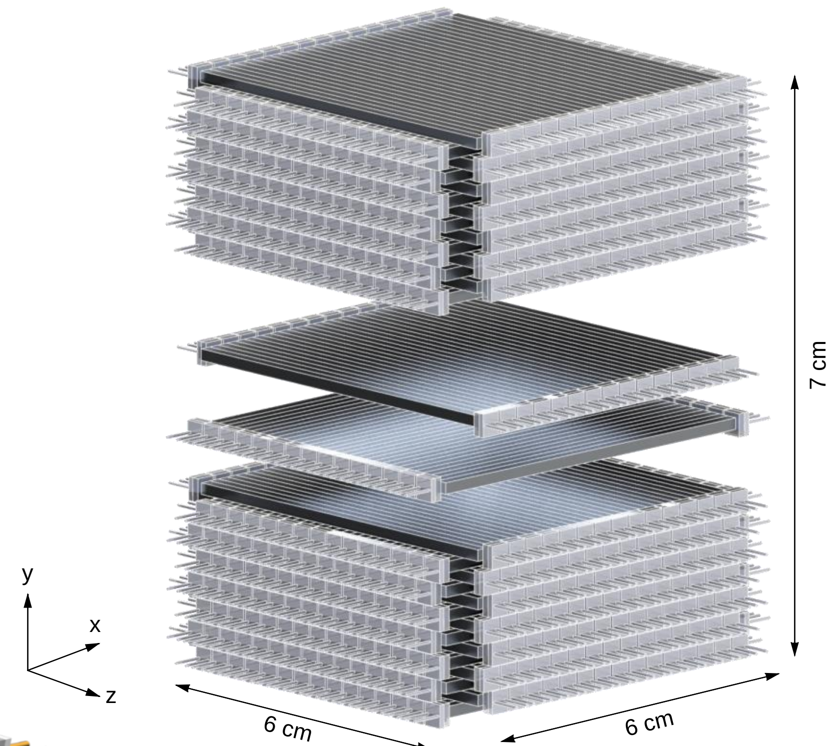
fully parallel readout electronics
time-over-threshold ASIC + FPGA architecture
high-rate capability

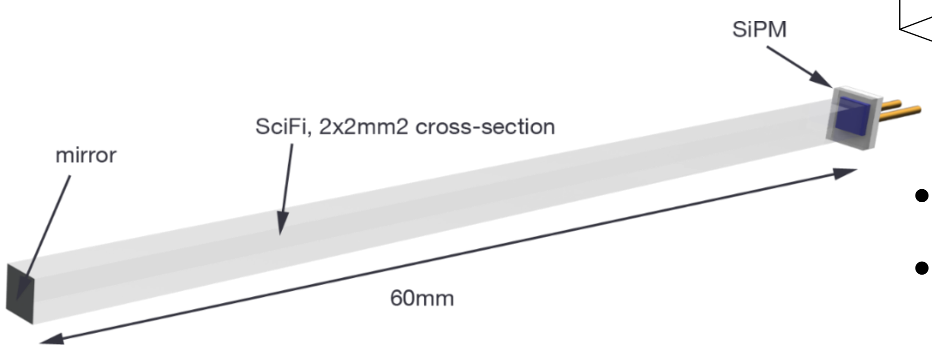


The Active Detection Unit

Setup

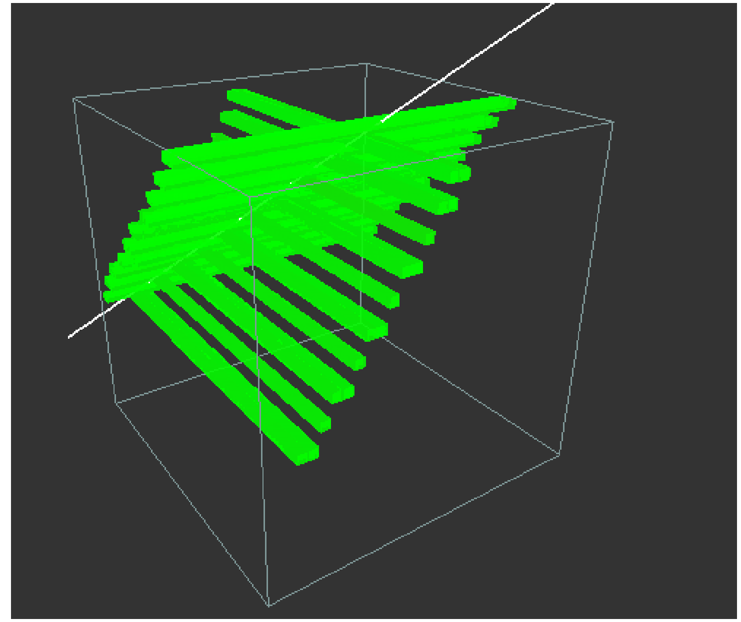
- 900-channel active-target calorimeter
- scintillating fibers coupled to silicon photomultipliers (SiPM)
- stacked in 30 layers of 30 fibers each
- 3D-tracking of charged particles





- SCSF-78 scintillating fibers (Kuraray)
- 3x3 mm² silicon photomultiplier from KETEK / Hamamatsu

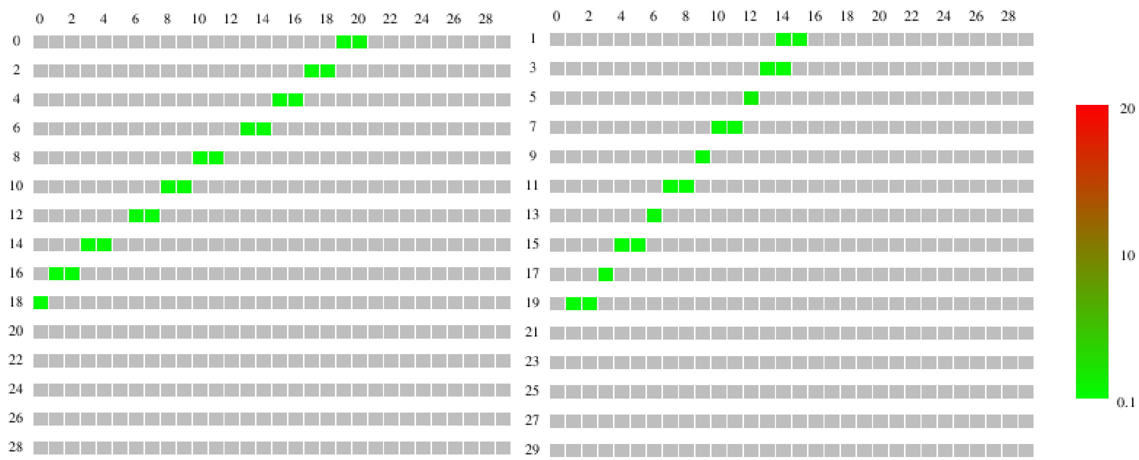
Event Reconstruction



Goal: reconstruct direction and particle characteristics (type, charge, energy) for individual events

Tracking

- 3D straight-line finding problem
- precise track fitting
  - Bayesian particle filter
  - Markov-Chain Monte-Carlo
- fast algorithms:
  - Hough transformation
  - neural network

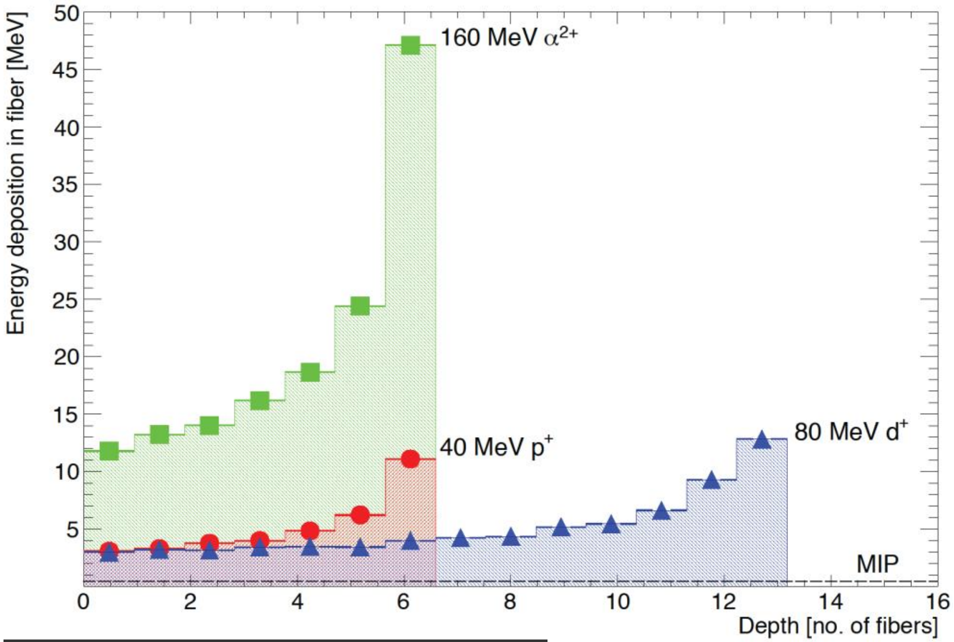


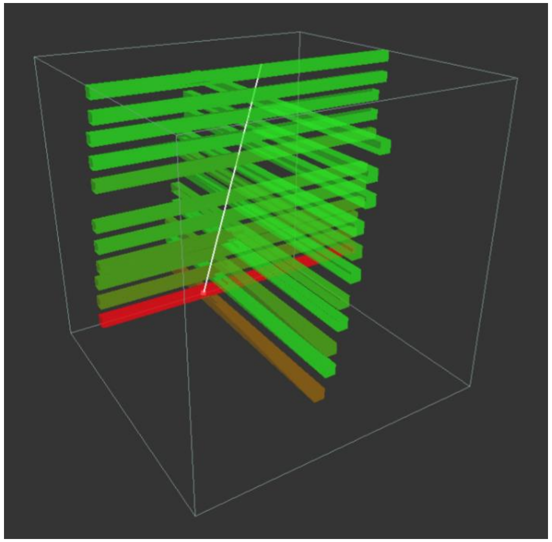
Event Reconstruction

Goal: reconstruct direction and particle characteristics (type, charge, energy) for individual events

Bragg Curve Spectroscopy

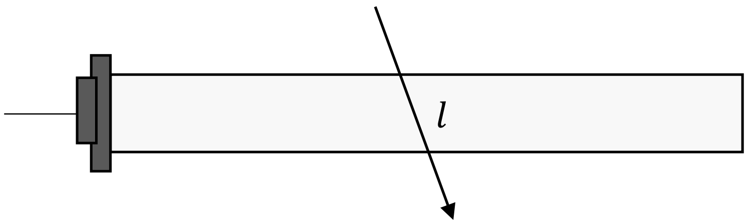
- energy-loss profile along the particle's track is unique for low-energy ions
- shape of profile depends on velocity, charge, and mass of the particle
- extrapolation of Bragg curve for through-going particles extends measurement range





Challenges of the Event Reconstruction

Response of Scintillator



$$Signal = Response(\Delta E)$$

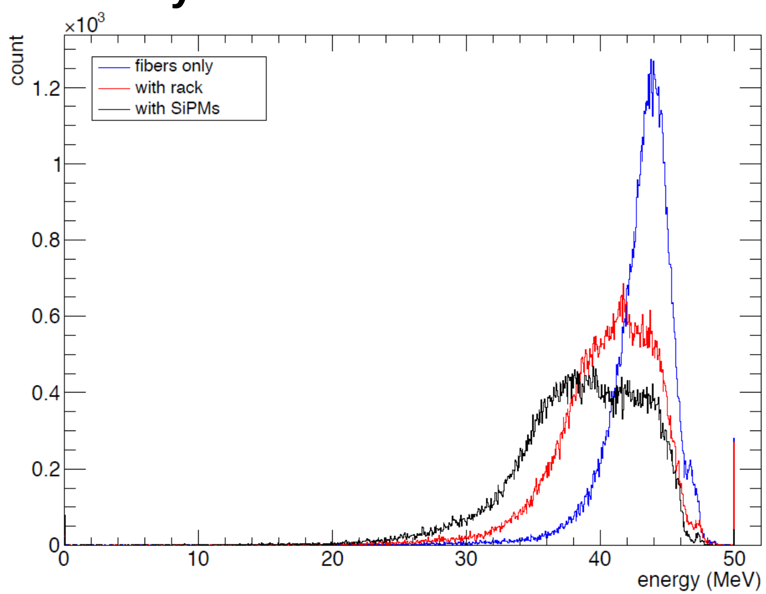
$$\Delta E = \int_l \left\langle \frac{dE}{dx} \right\rangle dx$$

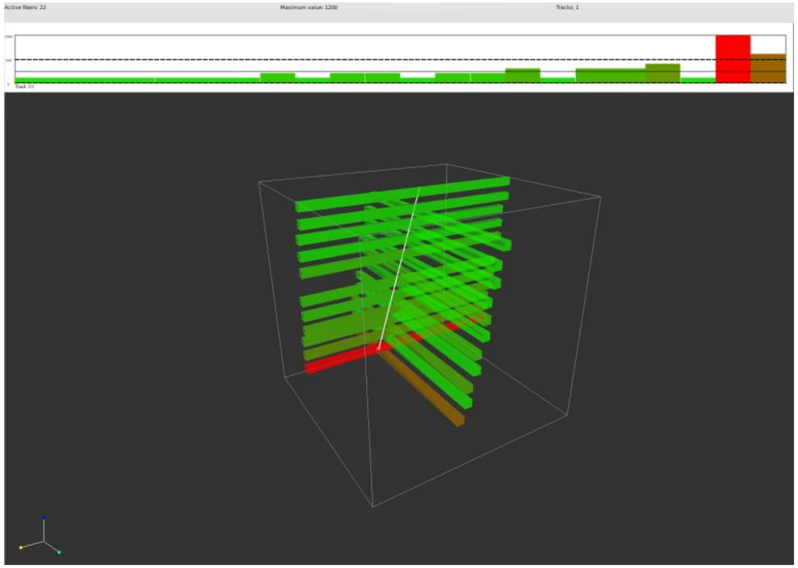
track length through fiber (geometrical)

particle characteristics (described by Bethe-Bloch eq.)

- combined fit of direction and particle characteristics necessary

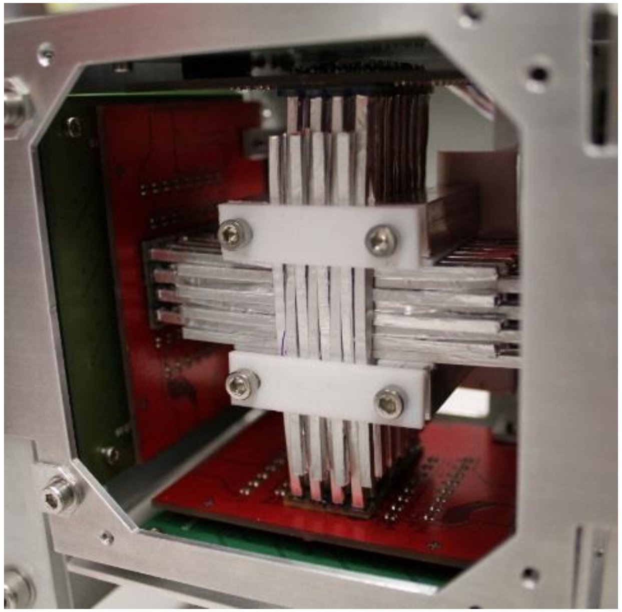
Dead Layers



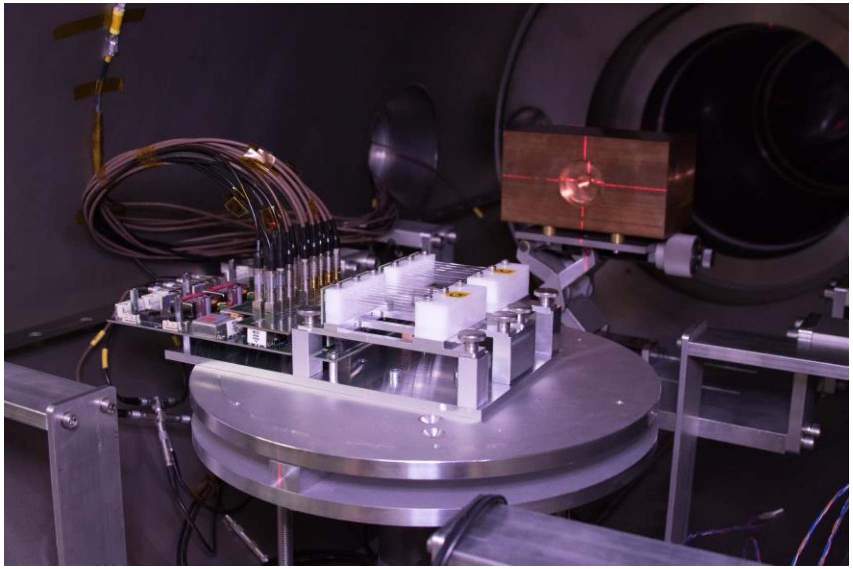


Response of the Fiber-SiPM Combination

- prototype tests at Paul-Scherrer Institute, Switzerland (2014, 2016)
- 16- and 128-channel prototypes
- measuring the response to minimum-ionizing pions and stopping protons
- show tracking capabilities of the setup
- measure response of fibers for different incidence angles



128-channel prototype

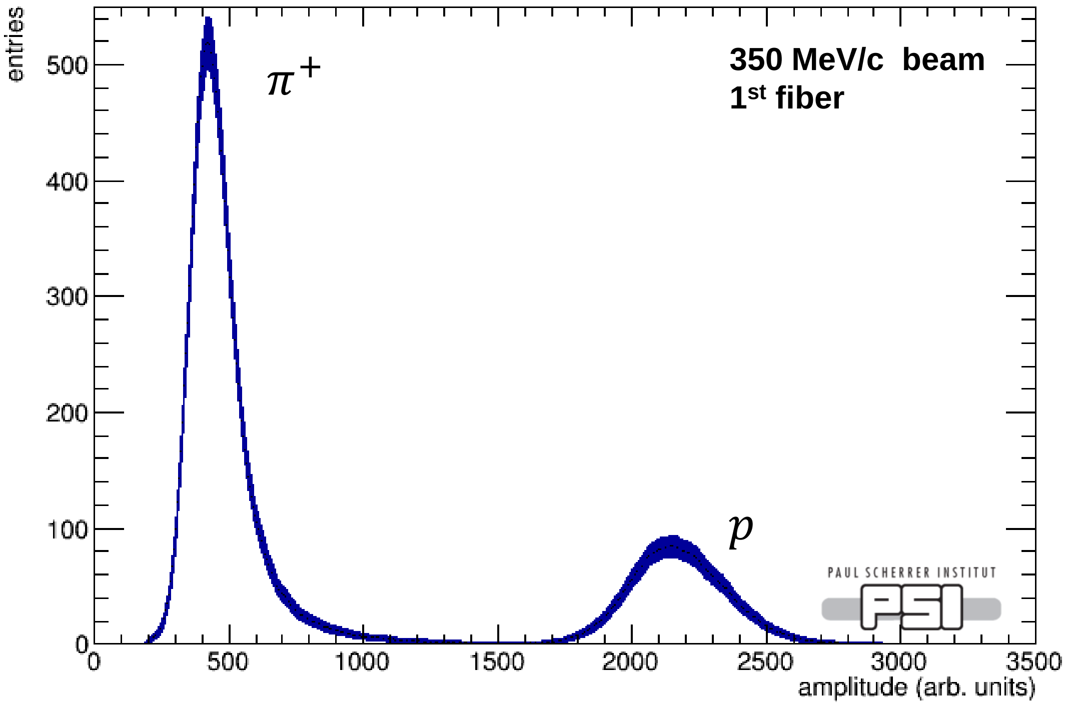


16-channel prototype with rotary table

Response of the Fiber-SiPM Combination

Results

- good signal-to-noise separation for minimal-ionizing particles (MIP)
- good separation of protons and pions at equal momentum
- ~220 photoelectrons per MeV energy deposition



Response of the Fiber-SiPM Combination

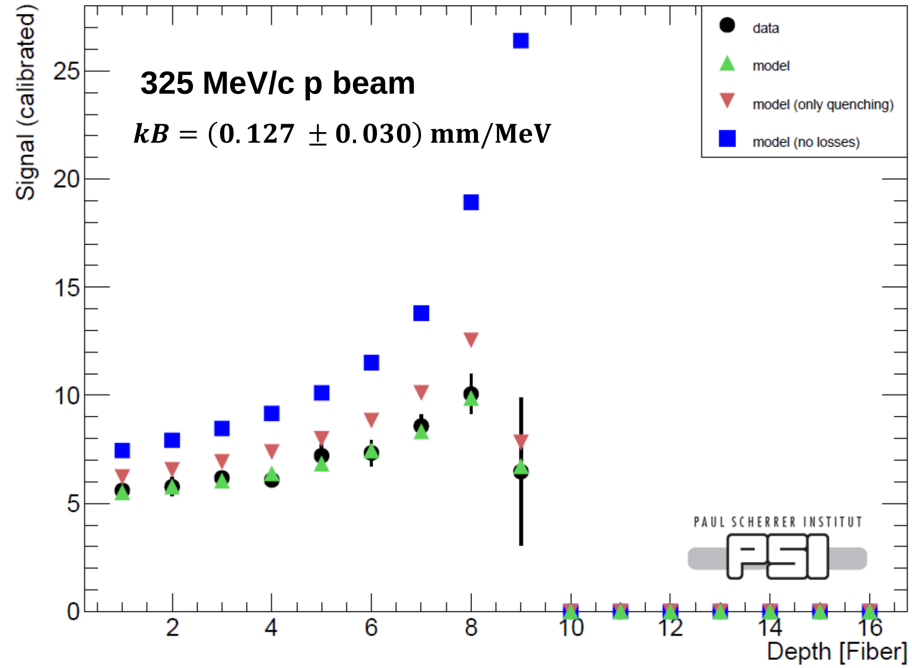
Results

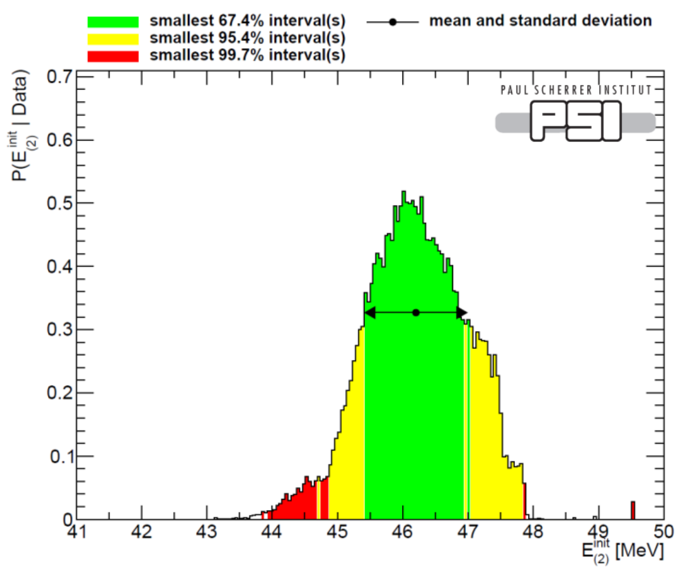
- quantification of signal-saturation effects
  - ionization (Birks') quenching

$$\left\langle\frac{dL}{dx}\right\rangle = \frac{\left\langle\frac{dE}{dx}\right\rangle}{1 + kB\left\langle\frac{dE}{dx}\right\rangle}$$

  - saturation of SiPMs

$$N_{\mathrm{av}} = N_{\mathrm{pixel}} \cdot \left(1 - e^{-\frac{\varepsilon_{\mathrm{PDE}} \cdot N_{\gamma}}{N_{\mathrm{pixel}}}}\right)$$





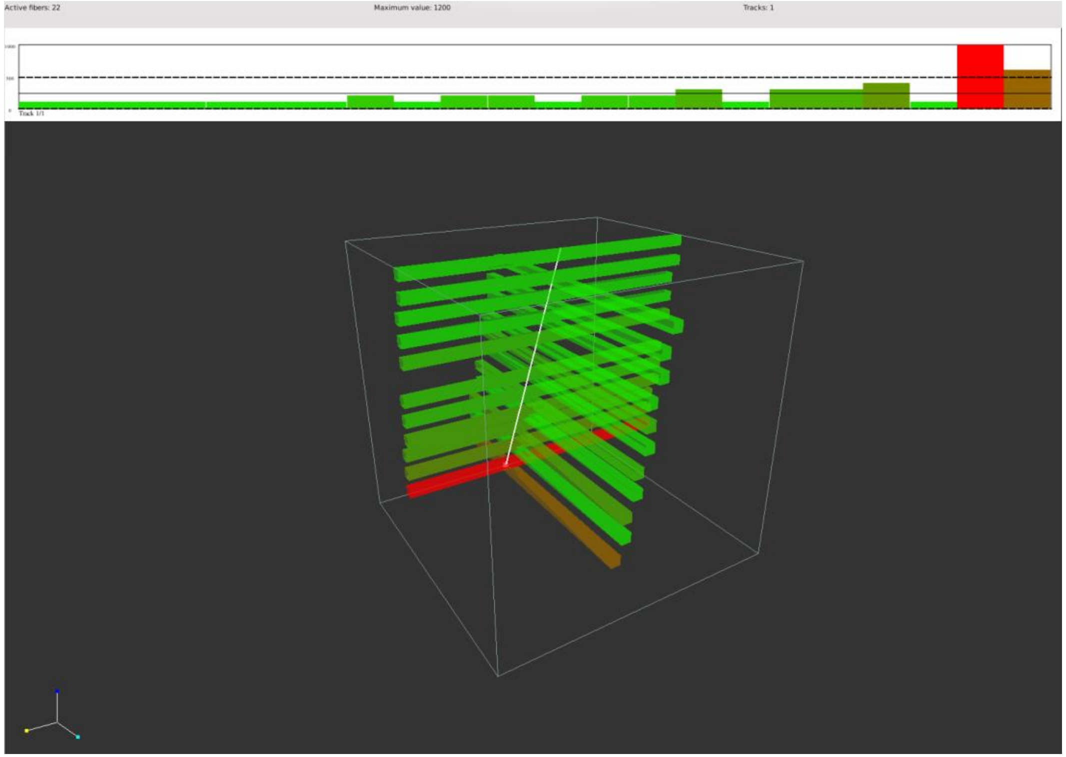
- precise reconstruction of the beam energy
  - sub-MeV precision between 50 to 75 MeV
  - limited by energy-straggling effects of the beam in front of the detector

Event Reconstruction: Bayesian Analysis Methods

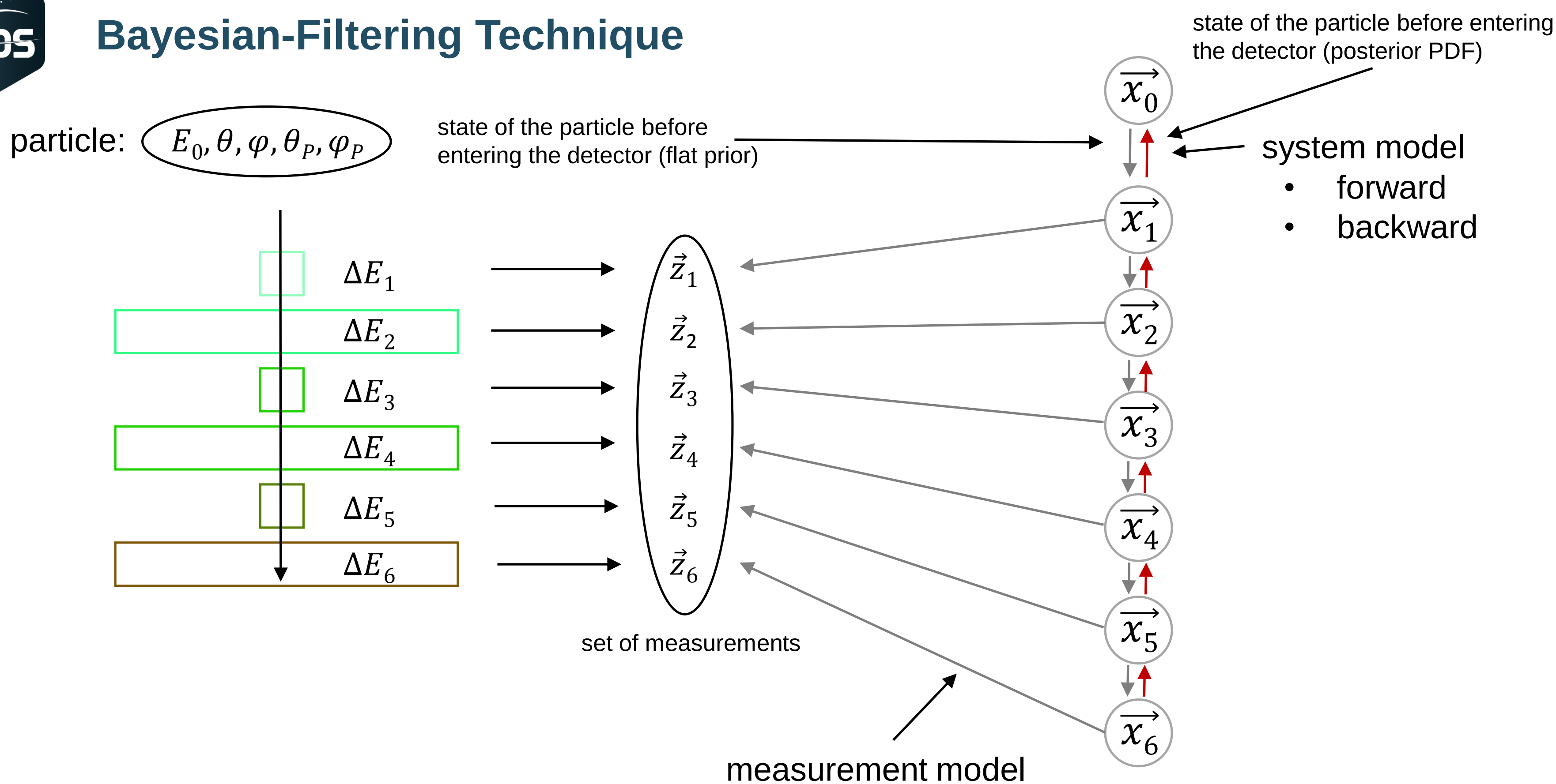
Goal: find posterior-probability density function (PDF) for individual event: $P\left(E_0, Z, A, \vec{\theta}\,\middle|\,\mathrm{Data}\right)$

Bayesian-Filtering Technique

Likelihood Models



Bayesian-Filtering Technique



- Integrating over all possible transitions from state $\overrightarrow{x_k}$ to $\overrightarrow{x_{k+1}}$, we can connect the underlying states to each other

$$P(\overrightarrow{x_k} | \overrightarrow{z_{k+1}}, \dots, \overrightarrow{z_N}) = \int P(\overrightarrow{x_k} | \overrightarrow{x_{k+1}})\, P(\overrightarrow{x_{k+1}} | \overrightarrow{z_{k+1}}, \dots, \overrightarrow{z_N})\, \mathrm{d}\overrightarrow{x_{k+1}}$$

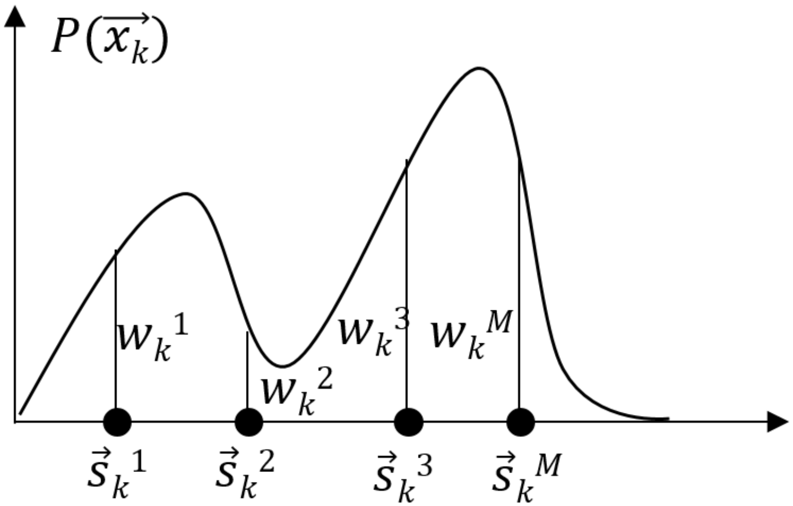
- recursively calculate the PDF until state $\overrightarrow{x_N}$ (after last measurement)

Bayesian-Filtering Technique: Implementation

- representation of PDF using 10k / 100k samples per step

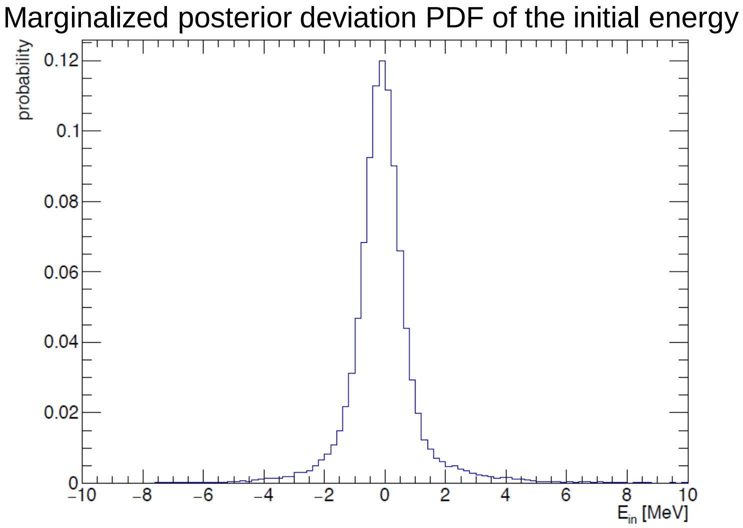
1) draw random set of samples $\{\overrightarrow{s_{k+1}^{1}}, \ldots, \overrightarrow{s_{k+1}^{M}}\}$ from PDF $P(\overrightarrow{x_{k+1}})$
2) apply system model for each sample (transition process)
   - geometrical transport using CAD imported data
   - multiple scattering
   - single coulomb scattering
   - energy loss including energy-loss fluctuations
3) re-weight samples using the measurement model

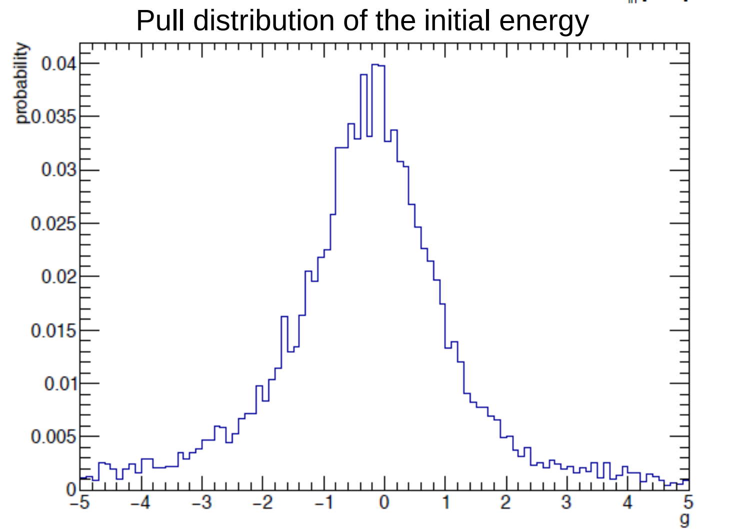
$$w_k^i = \frac{P(\overrightarrow{z_k} \,|\overrightarrow{s_k^{i*}})}{\sum_{j=1}^{M} P(\overrightarrow{z_k} \,|\overrightarrow{s_k^{j*}})}$$



Particle Filter Performance

- test with simulated data
  - 50 MeV protons
  - isotropic flux
  - including dead layers (PMMA, aluminum)
  - flat prior probability distributions for free parameters
  - 10 000 samples
- results
  - initial energy resolution: 2.5% (1.2 MeV)
  - initial direction resolution (3D): 3.1°
  - no bias in energy or direction
- drawbacks
  - computational performance (several CPU min per event)
  - not down-scalable for online reconstruction (~ms)
- possible upgrades
  - fast tracking algorithms for prior probability distributions
  - only backward filtering
  - implement geometric calculations on GPUs

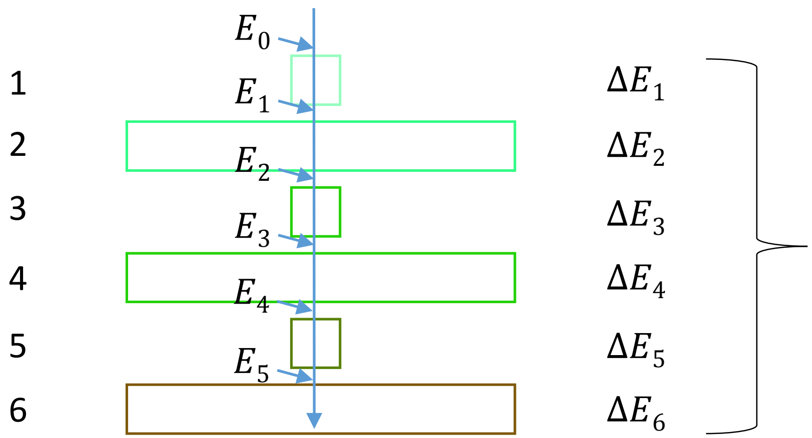




Likelihood Methods

- evaluation of likelihood for different levels of precision
  - maximum-likelihood fit (online) e.g. simulated annealing, gradient following,…
  - full PDF extraction using Markov-Chain Monte-Carlo
- implemented using the Bayesian Analysis Toolkit (https://github.com/bat/bat)

Likelihood Formulation



energy deposition in each fiber treated as nuisance parameters

probability to produce a measurement $\boldsymbol{\varepsilon_i^{(d)}}$ in fiber $\boldsymbol{i}$:

measurement prediction: $P_{pred} = S(\Delta E_i | E_{i-1}, l_i)$,
$S \equiv$ Straggling function

measurement noise: $P_{noise} = P\left(\varepsilon_i^{(d)} \middle| \varepsilon_i \ , \sigma_i\right)$

overall probability: $P = P_{pred} \cdot P_{noise}$

Likelihood Methods

Full Logarithmic Likelihood

$$\log L = \sum_{i=1}^{i=N} \left(\log P\left(\varepsilon_i^{(d)} \middle| \Delta E_i, \sigma_i\right) + \log S(\Delta E_i | E_{i-1}, l_i)\right)$$

Results

- results comparable to particle filter
- computational effort larger than for particle filter
- simulated annealing + gradient following fastest method but still $\mathcal{O}$(CPU min)

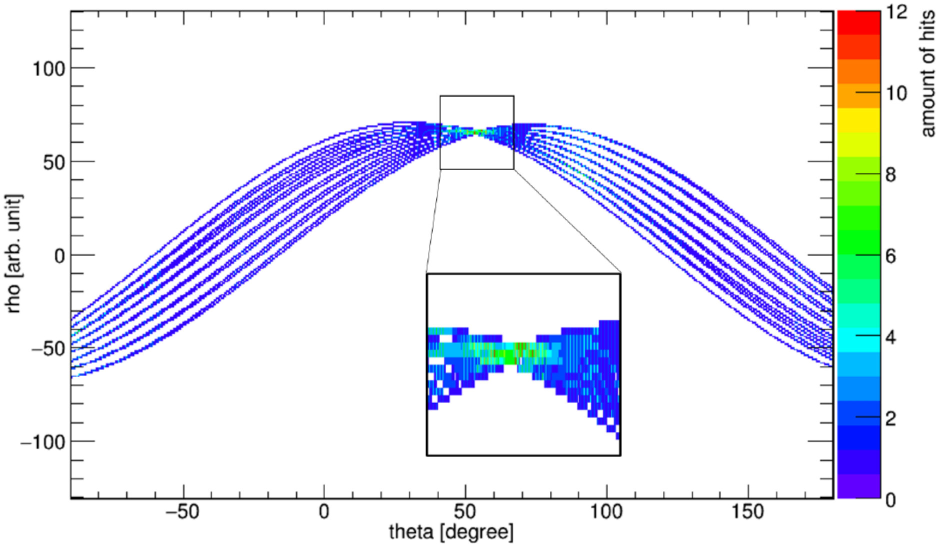
Fast Methods for Online Reconstruction and Triggering

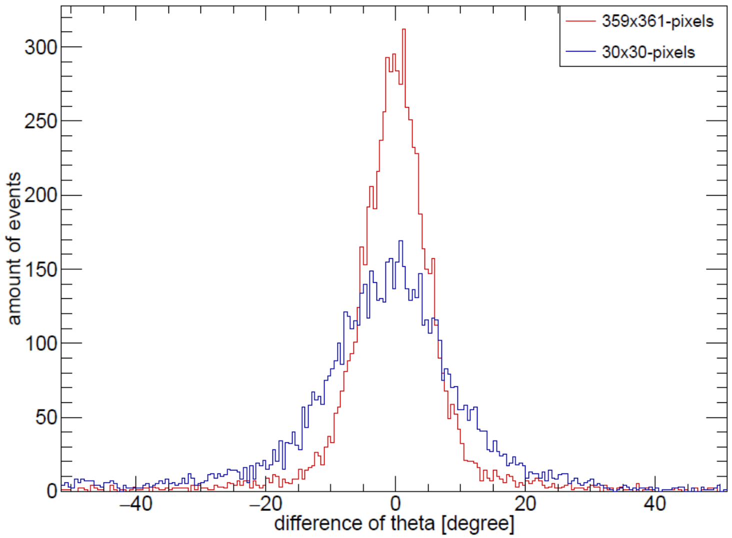
- reconstruct 2D tracks independently and combine afterwards to exploit lower dimensionality and enable parallel reconstruction
- based on image-reconstruction methods

Hough Transformation

- treating a fiber as a pixel (15x30 pixel image)
- normally used for structures that are larger than pixel size
  - peak spreading
  - loss of geometric features

➢ oversampling the image: using smallest features of the geometry to fix the image size (360x360 pixel)
  - one fiber is treated as 11x11 pixels
  - increases precision





Fast Methods for Online Reconstruction and Triggering

Recent Idea: Neural Networks

- supervised learning with simulation data
- offline training of network and implement trained network for online analysis in the detector's DAQ
- simulation data from Geant4 contains a lot of features, since a lot of physics processes are implemented → no re-modelling of these processes necessary

Layout of the Neural Network

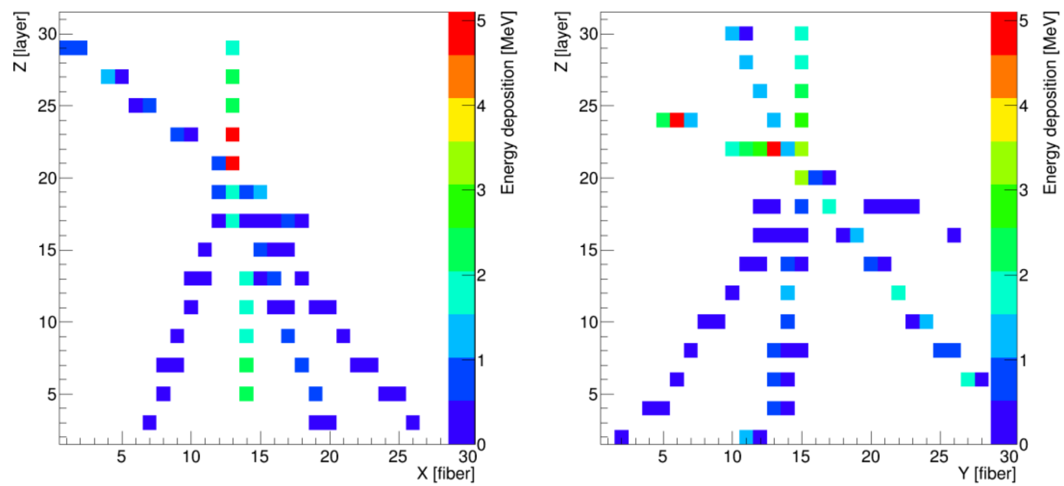
- joint network for parameter fitting ($E_0, \vec{\theta}$) and classification (Z, A)
- multilayered, convolutional network
- optimal design under investigation
- learning based on greyscale image

➢ **we would be delighted to get some input & ideas during this conference**

Conclusion

- a novel omnidirectional particle detector concept
- based on scintillating fibers coupled to SiPMs
- reconstruction of directionality and particle characteristics (particle type, energy, LET)
- implemented combined track fitting and particle reconstruction using Bayesian inference methods (offline analysis)
  - particle filter method
  - likelihood method
- fast algorithms for online analysis under investigation
  - Hough transformation
  - neural networks

- further use cases
  - medical proton-beam characterization and monitoring
  - cosmic-ray physics on stratospheric research balloons
  - anti-ion identification using the annihilation process in the active volume



Thank you for your attention!