Submodule- and Feature-Extraction-Tests

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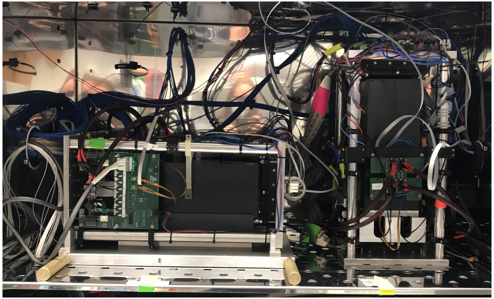
HISKP – University Bonn

Performance of submodules in standing and lying position

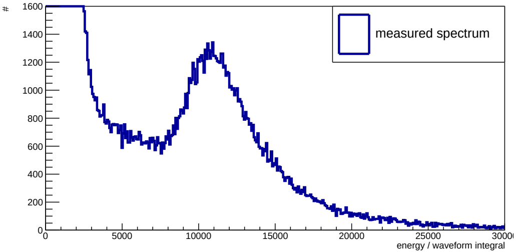
Submodule Test – Experimental Setup



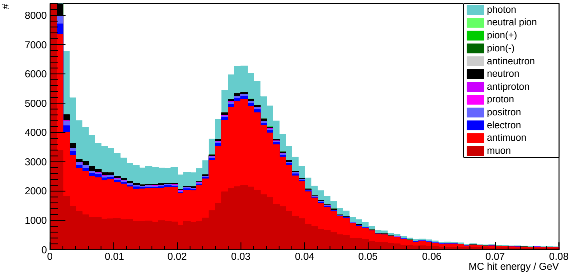
- energy deposition of **cosmics at −25 °C**
- submodule with APD readout
- HV-board + **SADC-readout** (2 FPGAs)
- compare cosmic peak position standing/lying
  → **RATIO**

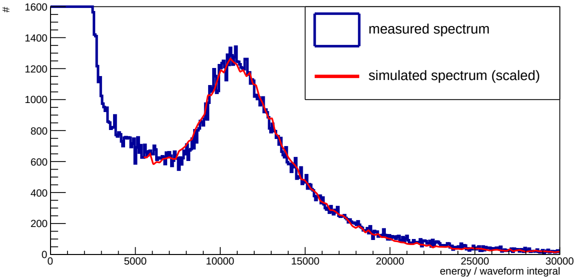
- different **path length** through crystal
  → **naively** expected ratio

$$R = \frac{\text{peak standing}}{\text{peak lying}} \approx \frac{200.0\,\text{mm}}{23.3\,\text{mm}} = 8.6$$



Monte-Carlo Simulation – Fit to Measured Data





- simplified geometry:
  → **Cry-generator**
  → passive material: air + concrete floor + ceiling
- **submodule** including 16 crystals
- spectrum for **standing and lying** submodule

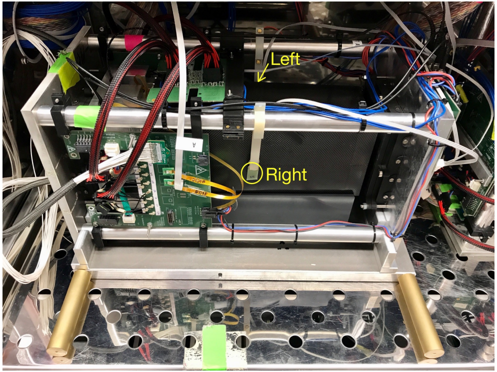
- fit MC-spectrum to measured data
  → obtain **x-scale factor**
  ⇒ nice consistency!
- naively expected **ratio**

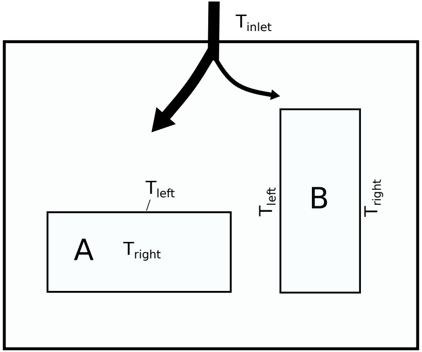
$$R = \frac{\text{x-scale standing}}{\text{x-scale lying}} = 1.0$$

Ratio of Cosmic Peak Position – Temperature Correction

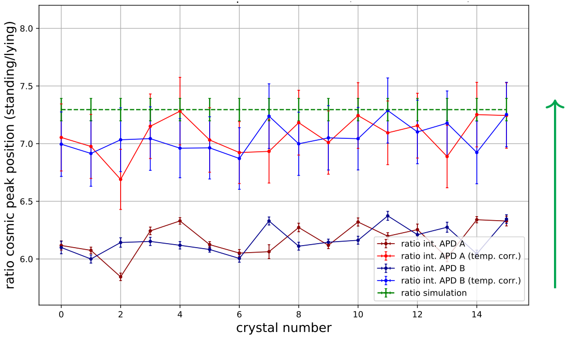
- correct for temperature deviation relative to −25 °C
  → **external sensors**
  → **THMP sensors**
  ⇒ temp. uncertainty has **big impact**

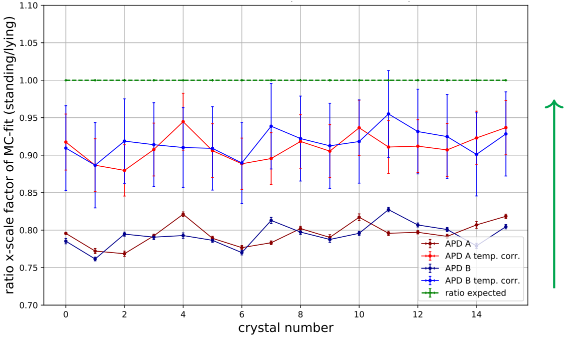
$$ADC_{\text{corr.}} = ADC_{\text{uncorr.}} \cdot \left(100\,\% - \underbrace{8\,\frac{\%}{\text{V}} \cdot 0.81\,\frac{\text{V}}{\text{K}}}_{\textbf{APD fact.}} - \underbrace{3\,\frac{\%}{\text{K}}}_{\textbf{LY fact.}} \right)^{\Delta T}$$





Cosmic Peak Ratio – External Temperature Sensors

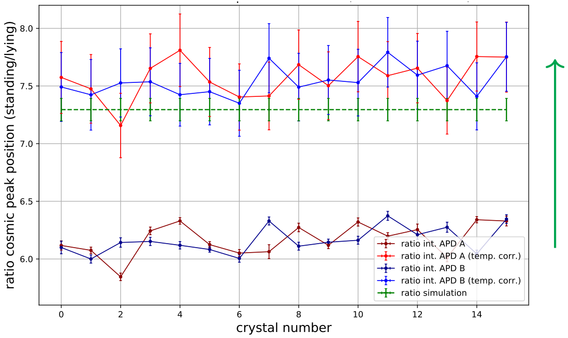


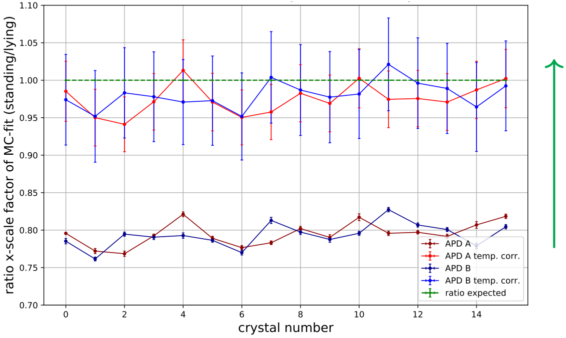


- peak position from **Landau-fit**
- external sensor temp. correction
  ⇒ mostly agree within uncertainty

- **x-scale** factor from **MC-fit** to meas. data
- external sensor temp. correction
  ⇒ do not agree within uncertainty

Cosmic Peak Ratio – THMP-Sensors



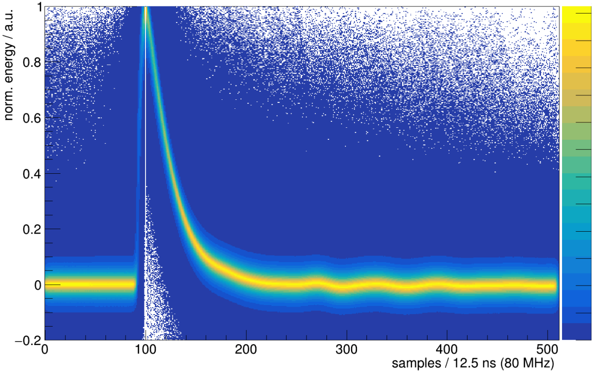


- peak position from **Landau fit**
- THMP sensor temp.
  ⇒ mostly agree within uncertainty

- **x-scale** factor from **MC-fit** to meas. data
- THMP sensor temp.
  ⇒ mostly agree within uncertainty

→ large impact of temp. uncertainty ⇒ **not possible to track down potential systematic effects**
⇒ in general **comparable performance**

Mean Waveform – Ringing



- measured waveforms from submodule tests
  ⇒ **mean-waveform**
- **"RINGING"** after pulse
  → **const. fraction** of pulse-height for **high-gain channel**
- origin of "ringing" visible in **preamplifier** pulse

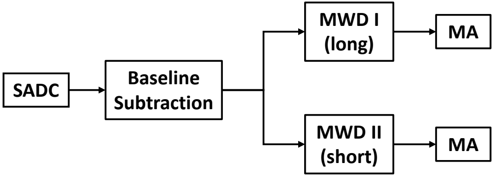
→ currently ringing considered to be not fixable
⇒ issue for feature-extraction

Feature-Extraction

PandaRoot Implementation of the Feature Extraction

1. Get **raw SADC-pulse**
2. Calculate mean of first 50 samples
   → **remove baseline**-offset
3. Apply Moving Window Deconvolution (**MWD**):
   → "remove" tail of pulse
   - Window length $m = 20$ (long) or $m = 10$ (short)
   - Decay constant of pulse $\tau \to$ fit
4. Apply Moving Average filter (**MA**):
   → smoothing
   - Window length $\mathbf{L} = \frac{\mathbf{m}}{\mathbf{2}}$

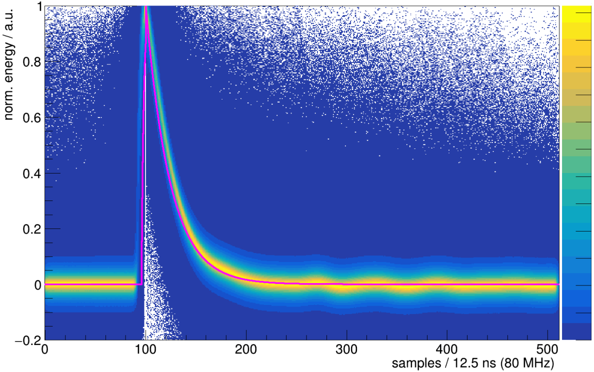
→ need to **characterize pulse-shape**!
⇒ **decay time**



$$\mathrm{MWD}_m[n] = x[n] - x[n-m] + \frac{1}{\tau} \sum_{k=n-m}^{n-1} x[k]$$

$$\mathrm{MA}_L[n] = \frac{1}{L} \sum_{k=0}^{L-1} x[k]$$

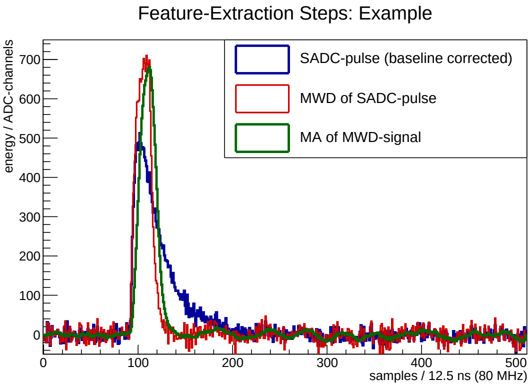
Lightpulser- and Cosmic-Waveform



- OLD: **lightpulser waveform**
  → perfect exponential behavior
  ⇒ optimal input for MWD
- NEW: **cosmic waveform** from submodule tests at −25 °C
  → not perfectly exponential
  → visible ringing

⇒ new waveform much more **realistic**

Moving Window Deconvolution - Drawback



- **"Ringing"** of waveform clearly visible after Moving-Average filter
  → distortion of energy-value in pile-up case
- **exponential tail** at falling edge of filtered waveform
  → increases PU-rate

⇒ **Wiener Deconvolution** developed for CB/ELSA
→ Requirement: constant waveform

Wiener Deconvolution

Basic Idea:

$$f = g * h \xrightarrow{\mathfrak{F}} \hat{f} = \hat{g} \cdot \hat{h}$$

$$\Big\downarrow :\hat{f} : \hat{h}$$

$$H = \mathfrak{F}^{-1}\left[\frac{\hat{g}}{\hat{f}}\right] \xleftarrow[\mathfrak{F}^{-1}]{} \frac{1}{\hat{h}} = \frac{\hat{g}}{\hat{f}}$$

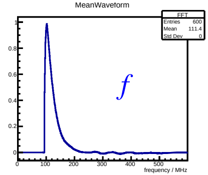
[Jan Schultes]

Deconvolution:

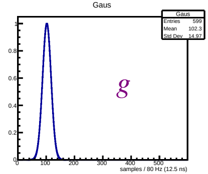
deconvolution of each measured waveform using H

$$g_{\text{event}} = f_{\text{event}} * H$$

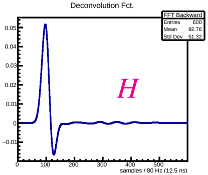
$\Rightarrow$ obtain chosen fct. g + noise



- **mean waveform** of raw SADC-pulse

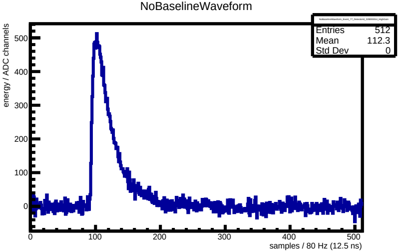


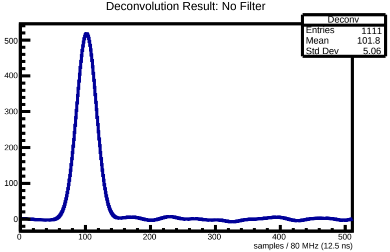
- **gaussian** fct. $\rightarrow$ chosen
  $\rightarrow$ σ limited by max. frequency
  $\rightarrow$ A to conserve peak-height



- **deconvolution** fct. H
  $\rightarrow$ determine **once**!

Wiener Deconvolution – Single Event Example





- ”deconvolution” in principle a **discrete convolution** with H for every SADC-waveform

  → technically comparable to MA- or FIR-filter
  ⇒ **viable for VHDL-implementation**

$$\mathrm{WD}[n] = (f * H)[n] = \sum_k f[k] \cdot H[n-k]$$

- **systematic ringing heavily suppressed** (low frequency noise still existent)
- Wiener deconvolution has **intrinsic filter property** → no further filtering (e.g. MA or FIR) necessary
- single crystal **energy resolution** slightly better than for MWD

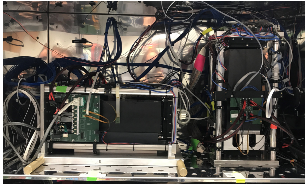
Summary and Outlook

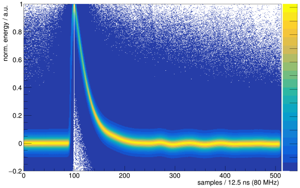
Summary:

- **comparable performance** of submodules in standing and lying position
- **temperature uncertainty** has too big impact to track down individual aspects
- **ringing** of SADC-pulseshape probably caused by preamp.
- new ansatz for **feature-extraction** may eliminate effect of ringing

Outlook:

- measure second submodule and test performance
- further **investigate ringing**
  → VPTT submodule
  → low-gain channel
- further analyze feature-extraction ansatz
  → **pile-up rate** comparison
  → peak-finder, baseline- and time-pickoff algorithm





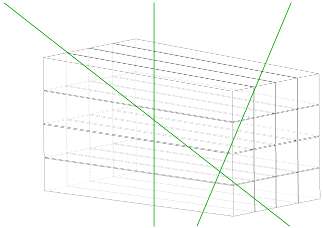
$$f = g * h \xrightarrow{\mathfrak{F}} \hat{f} = \hat{g} \cdot \hat{h}$$

$$\downarrow :\hat{f}\ :\hat{h}$$

$$H = \mathfrak{F}^{-1}\left[\frac{\hat{g}}{\hat{f}}\right] \xleftarrow[\mathfrak{F}^{-1}]{} \frac{1}{\hat{h}} = \frac{\hat{g}}{\hat{f}}$$

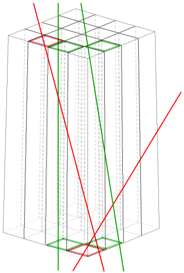
Backup

Submodule Tests – Data Selection



Lying submodule:

- **all tracks** allowed
  → every direction allowed
- get **waveform integral** of each crystal per event
  → fill values into histograms for each crystal
- **cosmic peak** at 31 MeV



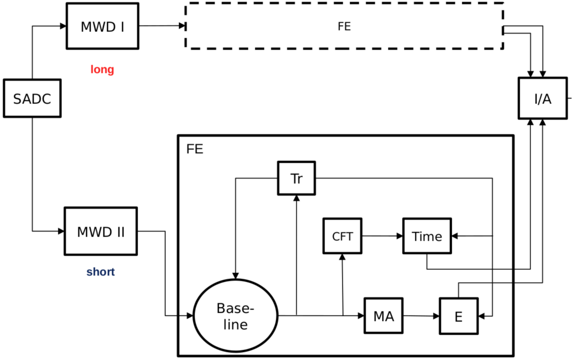
rejected tracks
accepted tracks

Standing submodule:

- select vertical hits – ”**single crystal events**”
- get waveform integral of each crystal per event
  → define **cut value** – no external trigger
  → one crystal above, remaining below
  → fill only integral of one crystal into histogram
- **cosmic peak** at 225 MeV

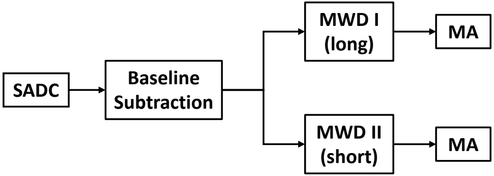
Online FE-Algorithm and Implementation in PandaRoot

Online FE based on TDR:



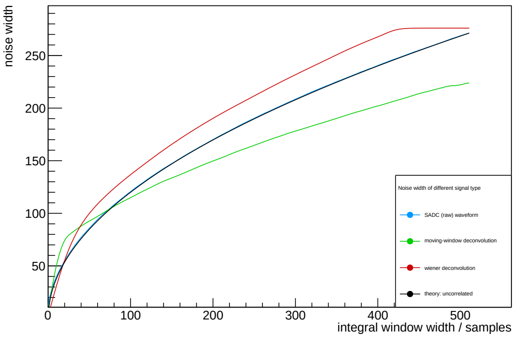
[Update to the Technical Design Report for the PANDA Electromagnetic Calorimeter, 2020]

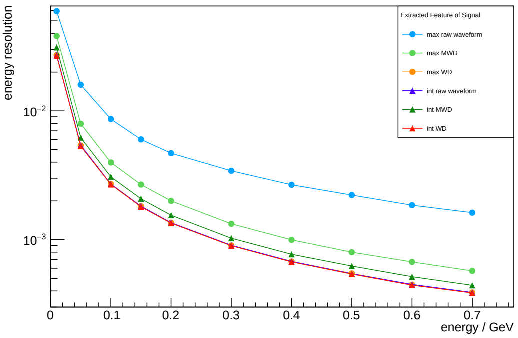
FE re-build in PandaRoot:



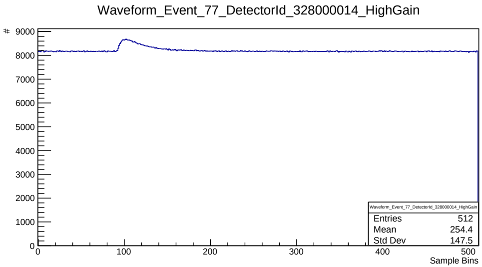
Energy Resolution – Comparison

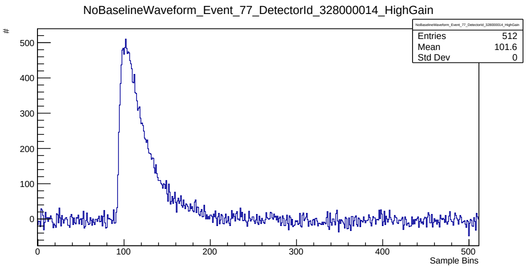
- simulate 100 000 of 0 GeV waveforms and extract width of **accumulated noise distribution**
  → get real noise width for **filtered signal**
  ⇒ get new integral boundaries via **optimizing S/N**
- simulate 100 000 waveforms for different energies and extract maximum and integral value
  → calculate energy-resolution

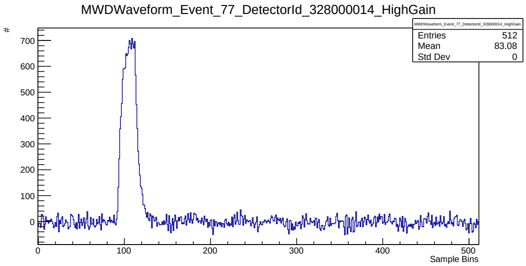


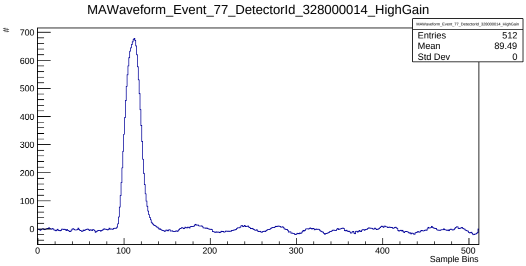


Moving Window Deconvolution - Single Event Example (Cosmics)

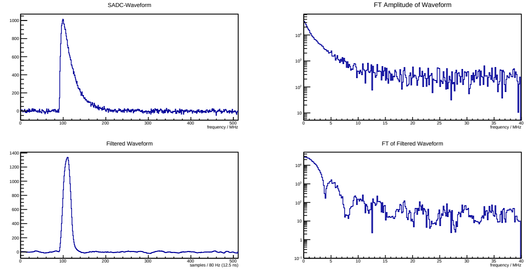


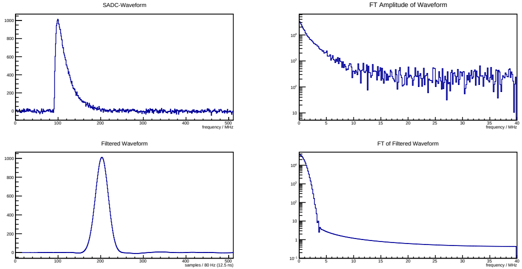


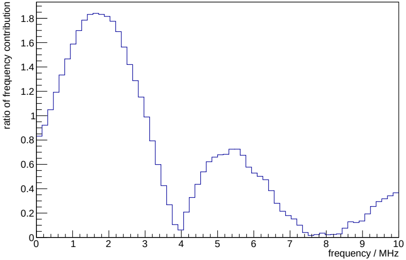


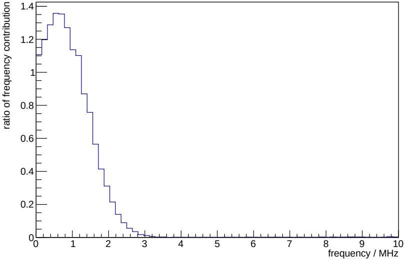


Frequency Behavior of Different Filters



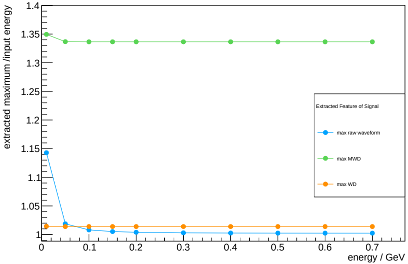




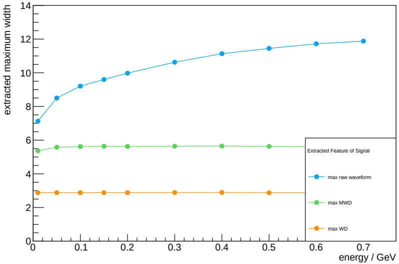


Maximum Feature

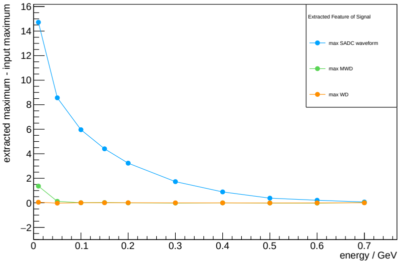
Maximum-feature normalized to maximum of input waveform



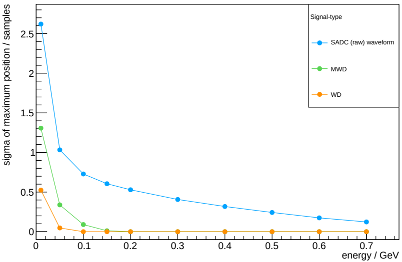
Width of maximum feature



Difference between maximum-feature and maximum of input waveform



StdDev of the extracted maximum-feature position



Integral Feature