Contents

1 Classical station triggers

As mentioned in **??**, continously analyzing data sent to CDAS from each of the 1600 SD water tanks would quickly exceed the computational capabilites of Augers' main servers. For this purpose, trace information is only collected from a station, once a nearby T3 event (c.f. **??**) has been detected. The formation of a T3 trigger is dependant on several T2, or station-level, triggers, which will be discussed in detail in this chapter. First, the implementation of different trigger algorithms is discussed in **??**. Their performance is evaluated in **??**.

1.1 Implementation

1.1.1 Threshold trigger (Th)

The **Th**reshold trigger (Th) is the simplest, as well as longest operating trigger algorithm [**triggerGuide**] in the field. It scans incoming ADC bins as measured by the three different WCD PMTs for values that exceed some threshold. If a coincident exceedance of this threshold is observed in all three WCD PMTs simultaneously, a Th-T1/2 trigger is issued. A pseudocode implementation of this algorithm is hence given by the below code block.

```
th1 = 1.75      // Th1 level threshold above baseline, in VEM
th2 = 3.20      // Th2 level threshold above baseline, in VEM

while True:

    pmt1, pmt2, pmt3 = get_next_output_from_WCD()

    if pmt1 <= th2 and pmt2 <= th2 and pmt3 <= th2:
        raise Th-T1_1trigger
    else if pmt1 <= th1 and pmt2 <= th1 and pmt3 <= th1:
        raise Th-T2_trigger
    else:
        continue
```

Logically, with increasing signal strength S in the PMTs, the likelihood of having observed an extensive air shower raises. This is reflected in the trigger level logic, where a coincident signal of $S \leq 3.20\,\mathrm{VEM}_{\mathrm{Peak}}$ is immediately forwarded to CDAS, whereas a signal $1.75\,\mathrm{VEM}_{\mathrm{Peak}} \geq S < 3.20\,\mathrm{VEM}_{\mathrm{Peak}}$ only raises a Th-T1 trigger. The algorithm is insensitive to signals that do not exceed at least $1.75\,\mathrm{VEM}_{\mathrm{Peak}}$ in all three PMTs.

In the case of faulty electronics, where only a subset of the WCD PMTs are available, the trigger thresholds (in units of $\mathrm{VEM}_{\mathrm{Peak}}$) are updated according to **??**.

Table 1.1: Numerical values from [**triggerSettings**]

n_{PMT}	Th-T2	Th-T1
1	5.00	2.85
2	3.60	2.00
3	3.20	1.75

1.1.2 Time over Threshold trigger (ToT)

The **T**ime **o**ver **T**hreshold trigger (ToT) is sensitive to much smaller signals than the Threshold trigger discussed in **??**. For each PMT in the water tank, the past 120 bins are examined for values that exceed 0.2 $\mathrm{VEM}_{\mathrm{Peak}}$. If 13 or more bins above the threshold are found in the window - ordering or succession do not matter - the PMT is considered to have an elevated pedestal. The ToT trigger requires at least two PMTs with an elevated pedestal in order to activate. As such, the algorithm is theoretically sensitive to events that deposit just 0.5 $\mathrm{VEM}_{\mathrm{Ch.}}$ A pseudocode example is given below.

```
threshold   = 0.2  // pedestal threshold, in VEM
n_bins      = 12   // number of bins above pedestal
window_size = 120  // considered window length

buffer_pmts = [[False for i in 1..window_size] for j in 1..3]
step_count = 0

while True:

    pmts = get_next_output_from_WCD()
    buffer_index = step_count % window_size
    count_active_PMTs = 0

    for pmt, buffer in pmts, buffers:
        if pmt <= threshold: buffer[buffer_index] = True

        if count_values(buffer, value = True) > n_bins:
            count_active_PMTs += 1

    if count_active_PMTs >= 2:
        raise ToT-T2_trigger
    else:
        step_count = buffer_index + 1
        continue
```

1.1.3 Time over Threshold deconvoluted trigger (Totd)

An extension to even lower signal strengths is given by the **ToT-d**econvoluted trigger (ToTd). As the name implies, the implementation of the algorithm is completely analog to the ToT trigger in **??**. Only the FADC input stream from the three PMTs is altered according to **??**.

$$d_i = (a_i - a_{i-1} \cdot e^{-\Delta t/\tau}) \,/\, (1 - e^{\Delta t/\tau}) \tag{1.1}$$

In **??**, the deconvoluted bin d_i is calculated from the measured FADC values a_i and a_{i-1}, where a_{i-1} is scaled according to an exponential decay with mean lifetime $\tau = 67\,\text{ns}$. This reduces the exponential tail of an electromagnetic signal to a series of pulses which in the case of $a_{i-1} < a_i$ exceed the original signal strength. As such, the deconvoluted trace can satisfy the ToT trigger requirements, whereas the original raw FADC values might not have, extending the sensitivity of the ToT trigger to lower signal strengths. The scaling constant $\Delta t = 25\,\text{ns}$ is tied to the sampling rate of UB electronics (c.f. **??**). The choice of the numerical constants τ and Δt is explained in more detail in [**ToTtriggerIdea**].

1.1.4 Multiplicity of Positive Steps (MoPS)

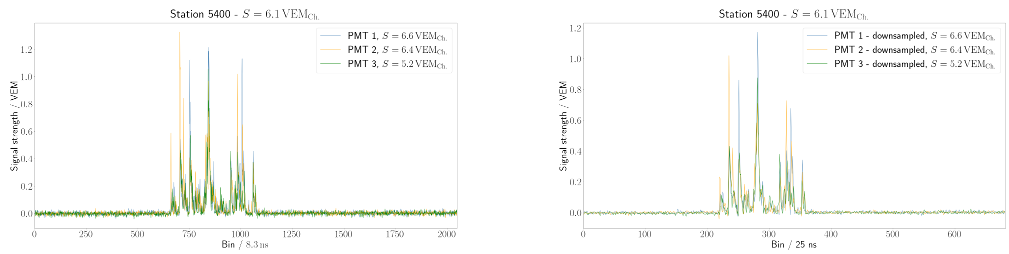
The **M**ultiplicity **o**f **P**ositive **S**teps (MoPS) algorithm triggers on positive flanks of an FADC trace, which can be related to the arrival of new particles in the water tank.

A positive flank in the FADC trace of a single PMT is any combination of at least two bins that are monotonically increasing in value, in a window of 120 bins. Once such a positive step has been identified, a (MoPS) trigger veto is applied to the next

$$n_{\text{skip}} = \lfloor \big(\log_2(\Delta y) + 1\big) - 3 \rceil \tag{1.2}$$

bins, where Δy refers to the total vertical increase in the step from first to last bin. Note that in **??** the notation $\lfloor x \rceil$ is used as shorthand notation to round x to the nearest integer. If Δy is bigger than $y_{\text{min}} = 3\,\text{ADC}$ (to filter random fluctuations), but does not exceed $y_{\text{max}} = 31\,\text{ADC}$ (to prevent triggering on muonic coincidences), it is added to a ledger. If the number of rising flanks in the ledger is bigger than $m > 4$ for at least two PMTs, a final check regarding the integral of the FADC trace is performed. If this check passes, a MoPS-T2 trigger is issued to CDAS. An in-depth discussion of the different hyperparameters for this trigger is offered e.g. in [**gapMoPS**].

It is impossible to accurately recreate the MoPS trigger in simulations. The integral test above compares the sum of the last 250 bins against a threshold ($\sum a_i > 75$). Since not all 250 bin values are available to CDAS, differing results are to be expected when comparing the implementation of the algorithm in the SD field versus its' counterpart in analysis software.



(a) UUB time trace **(b) UB time trace**

Figure 1.1: (a) A simulated signal as it would appear to UUB electronics. The ionizing particles originating in the extensive air shower hit the tank around bin 660 ($\approx 5.5\,\mu s$). **(b)** The same signal but filtered and downsampled to emulate UB electronics.

For this purpose, the MoPs trigger is not considered in the analysis presented in **??**. The implications of this choice are layed out in **??**.

1.1.5 Compatibility mode

Altough the triggers discussed in the previous subsections are meant to function completely autonomously in the SD field, their implementation requires some prior knowledge of the signal one desires to detect. For their use in the Auger observatory, several hyperparameters such as the thresholds of the Th-Trigger, or the window size of the ToT-trigger have been determined in studies ([**bertou2006calibration**], [**triggerSettings**], [**ToTtriggerSetting**]).

These studies were conducted using the predecessor, the **U**nified **B**oard (UB), of the hardware that is being installed during the AugerPrime upgrade of the observatory. Most importantly, the **U**pgraded **U**nified **B**oard (UUB) has a sampling rate that is three times larger (120 MHz) than that of UB electronics (40 MHz). Not only does this raise the number of bins in a standard time trace from 682 to $2^{11} = 2048$, but also drastically reduces the efficiency (in particular for ToT-like triggers) of the above discussed algorithms. Whereas a new FADC bin is measured every 25 ns in a UB station, the triggers would receive a new input every ≈ 8.3 ns in a UUB setting.

The modus operandi elected by the Pierre Auger collaboration to circumvent this problem is to emulate UB electronics using the UUB electronics. This means that measured FADC bins are to be filtered and downsampled before any trigger runs over them. Software implementations by which this is achieved are listed in **??**. The effect the filtering and downsampling has on measured data is visualized in **??**.

[to do: comment on accuracy fo this method]

1.2 Performance

The performance of a trigger can be evaluated in many different ways. In the most general consideration, a confusion matrix holds information about the ability of a classifier to discern between different types, or classes, C. With the example at hand there exist two types of events one wishes to distinguish, a signal event C_1 in the form of an extensive air shower, versus background C_0. The confusion matrix thus becomes:

		Predicted C	
		C_1	C_0
True C	C_1	True positive (TP)	False negative (FN)
	C_0	False positive (TP)	True negative (TN)

From this, other potentially interesting variables can be derived. Of particular interest for the Auger observatory are the sensitivity and **F**alse **D**iscovery **R**ate (FDR). The former is the probability that a signal event will be classified correctly, i.e. an extensive air shower hits a water tank and raises a T2 trigger. The sensitivity - in the following also called the trigger efficiency ϵ - is defined as

$$\epsilon = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}. \tag{1.3}$$

The latter is a measure of how readily the triggers (wrongly) identify background events like stray cosmic muons as extensive air showers. It is imperative for any trigger algorithm operating in the SD to minimize this probability. Simply due to the number of operating stations in the field, a small increase in FDR drastically raise the amount of potential events and hence load on the central analysis server of the observbatory.

$$\mathrm{FDR} = \frac{\mathrm{FP}}{\mathrm{TP} + \mathrm{FP}}. \tag{1.4}$$

[to do: continue writing about performance]

2 Neural network training data

Over their relatively brief existance, neural networks have been shown to perform increasingly impressive tasks (e.g. [**openai2019dota**], [**openai2023gpt4**], and many more). However, they learn by example. The performance of a neural network is directly linked to the input data it receives during training. If the training data is not an accurate example of real world information a network later operates on, insight gained from it is at best an approximation, and at worst completely randomly generated data.

As such, it is not a question *if* some neural network architecture can learn to identify an extensive air shower from WCD data, but rather which implementation, fed with which information, does. For this purpose, this chapter explains the procedure with which training data is generated. As stated above, this must occur with a focus on being representative of data actually measured in the SD array. The elected approach to create time traces is modularized. The structure of this chapter reflects this. First, general comments about the characteristics of background data (i.e. the WCD detector response in the absence of an extensive air shower) are made in **??**. Next, the process to extract signal originating from CRs is detailed in **??**. Lastly, building the time trace from the aforementioned modules and drawing samples from it for a neural network to train on is done in **??**.

2.1 Background dataset

While a flux of partices causes elevated ADC levels in both the HG and LG channels of a WCD PMT during a shower event, the lack of such a phenomenon does not imply the readout information is uniformly flat. Instead, it hovers around the channels' baseline (c.f. **??**) with occasional spikes upwards due to low-energy particles impinging on the detector. Coupled with electronic noise from the many digital components in the UUB, this constitutes the data that is collected inbetween air shower events.

2.1.1 Accidental muons

Most low-energy background particles present in the detector are muons. These are produced in the upper atmosphere during cascading processes analog to **??**. Due to the low primary energy the electromagnetic component of the shower is thermalized before it reaches surface level. The muonic component by itself does not contain enough information to enable an accurate reconstruction of primary energy and origin. This fact, coupled with the high flux of events at lower energies ($\Phi|_{E=100\,\mathrm{GeV}} \approx 1\,\mathrm{m}^{-1}\,\mathrm{s}^{-1}$ [**boezio2000measurement**]) make these events unsuitable for analysis. Stray muons,

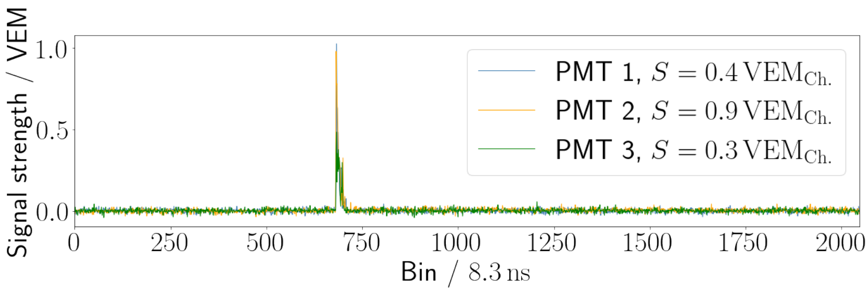


Figure 2.1: The simulated time trace from a single muon. The maximum peak of the time trace is equal $1\,\mathrm{VEM_{Peak}}$. The integrated signal S is of comparable magnitude.

even though they originate from extensive air showers, must consequently be considered background events.

The rate at which such particles traverse a WCD tank is $f_{\mathrm{Acc.}} \approx 4.665\,\mathrm{kHz}$ [**DavidInjectionFrequency**]. Their arrival time is Poisson-distributed. This implies that generally, one in 14 time traces contains signal from a low-energy background event. Coincidences of two accidental muons occur on a sub-percent level. Any higher order of coincidences is likely originating from a single air shower process. The typical signal recorded by the surface detector from a single muon is presented in **??**

2.1.2 Electronic noise

Electronic noise is the umbrella term given to the distortions that some signal is subject to during digital readout. Such noise can have many different origins. An illustrative example is given by the **L**aser **I**nterferometer **G**ravitational wave **O**bservatory, which excludes the 60 Hz band and its' harmonics from analysis. This is owed to the fact that the DC frequency standard in the United States introduces systematic uncertainties in the detector [**martynov2016sensitivity**]. In the electronics of Pierre Augers' SD array, electronic noise is assumed to be Gaussian. That is to say that the ADC values of a time trace that was measured while no particle produced signal in the tank are normally distributed around the baseline. The standard deviation can be estimated from monitoring data, as is shown in **??**. [to do: make this plot]

2.1.3 Random traces

Both above mentioned phenomena can be simulated, and the simulation results used as background training data for the neural networks discussed in the next chapter. A more accurate method, and the approach elected for this work is to utilize directly measured data from the field. Thanks to the work of David Nitz, there exist collections of so called random traces that were gathered by forcing DAQ readout via a manually set trigger. In particular,

./plots/standard_deviation_baseline.png

Figure 2.2: The variance of all UUB stations in the surface detector array. This data is collected from monitoring processes that forward station diagnostics to CDAS every five minutes. The data shown in this plot was recorded on the 15th Nov. 2022.

Characteristics

Calibration

[to do: citing?] [to do: spectral density]

2.2 Signal dataset

2.3 Trace building & Sliding window analysis