Simplified *optimal* digital TRIGGER

with guidelines
for experimental controls interaction

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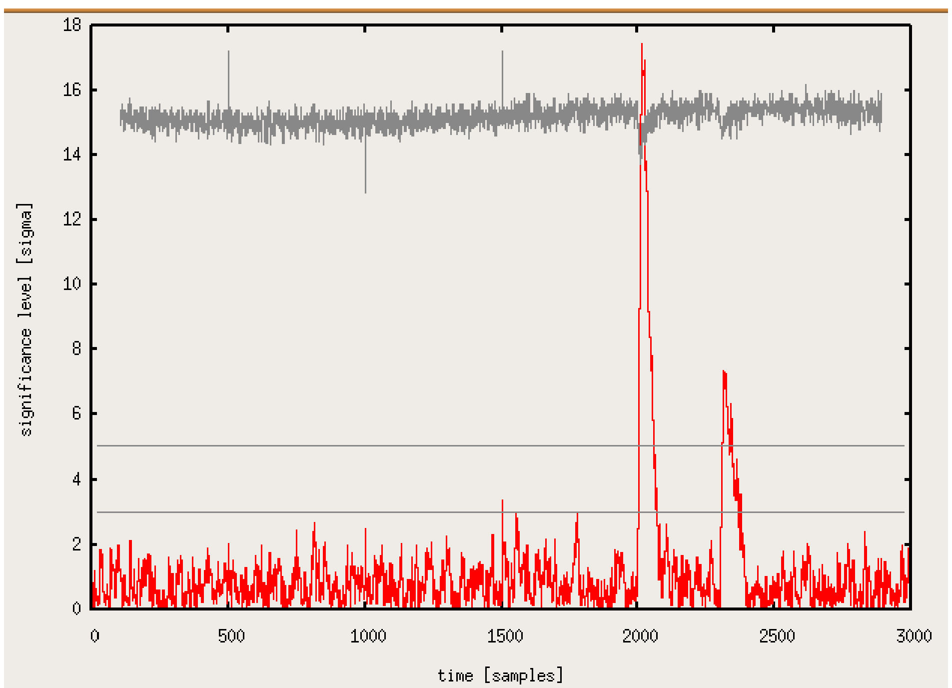
SGFDC meeting
Groningen, December 2007



- optimal recursive baseline follower:

  bimodal Kalman trigger

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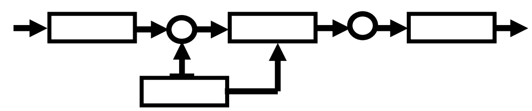
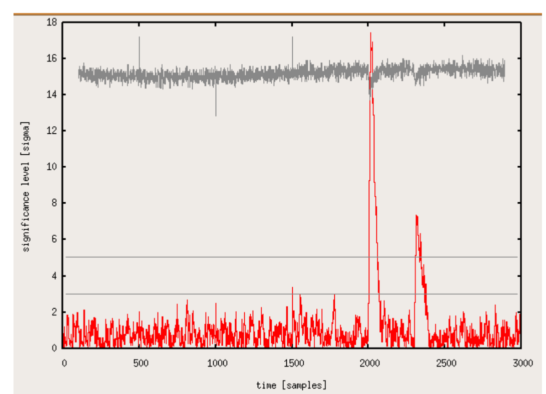
- Requirements & Task Description of Trigger Algorithm



- Construction & Principle of Simplified *Optimal* TRIGGER
- An Example



What do we need the trigger for?

common points of possible applications

- master project: *online* detection system for monitoring gamma-emitting radionuclides suspended in municipal water pipes

  → one task: simplified optimal trigger algorithm

  → connect to DAQ & controls of new generation of nuclear physics user facilities: self-triggering of free-running ADCs

- COMMON POINTS & GOALS:

  → digital front end

  → huge number of experimental channels

  → interaction via controls

  → capable of self-calibration

What are the *real-time* requirements ?

Task description

- runs entirely in the fast process: FPGA
- capable of following a slowly fluctuating baseline
- reports current baseline value to the calorimetry function
- follows noise level of baseline (variance σ^2)
- higher single-point signal-to-noise ratio
- trigger level expressed in standard deviations of the baseline fluctuation
- immune to baseline pulling by the occurrence of a pulse

Construction of an optimal trigger

An approach

- OPTIMAL filter: estimate of desired variable from imprecise measurements in such a way that error is minimized statistically

- measurement 1 of constant x: x_1 with variance σ_1^2

- measurement 2 of constant x: x_2 with variance σ_2^2

  → estimate constant x: $\mathbf{x} = \sigma_2^2/[\sigma_1^2 + \sigma_2^2]\, x_1 + \sigma_1^2/[\sigma_1^2 + \sigma_2^2]\, x_2$

  → weighted average

  → estimate of variance of x: $\boldsymbol{\sigma_x^{-2}} = \sigma_1^{-2} + \sigma_2^{-2}$

- system dynamics: variable propagation by "best" knowledge of system dynamics

Working Principle of Our Trigger

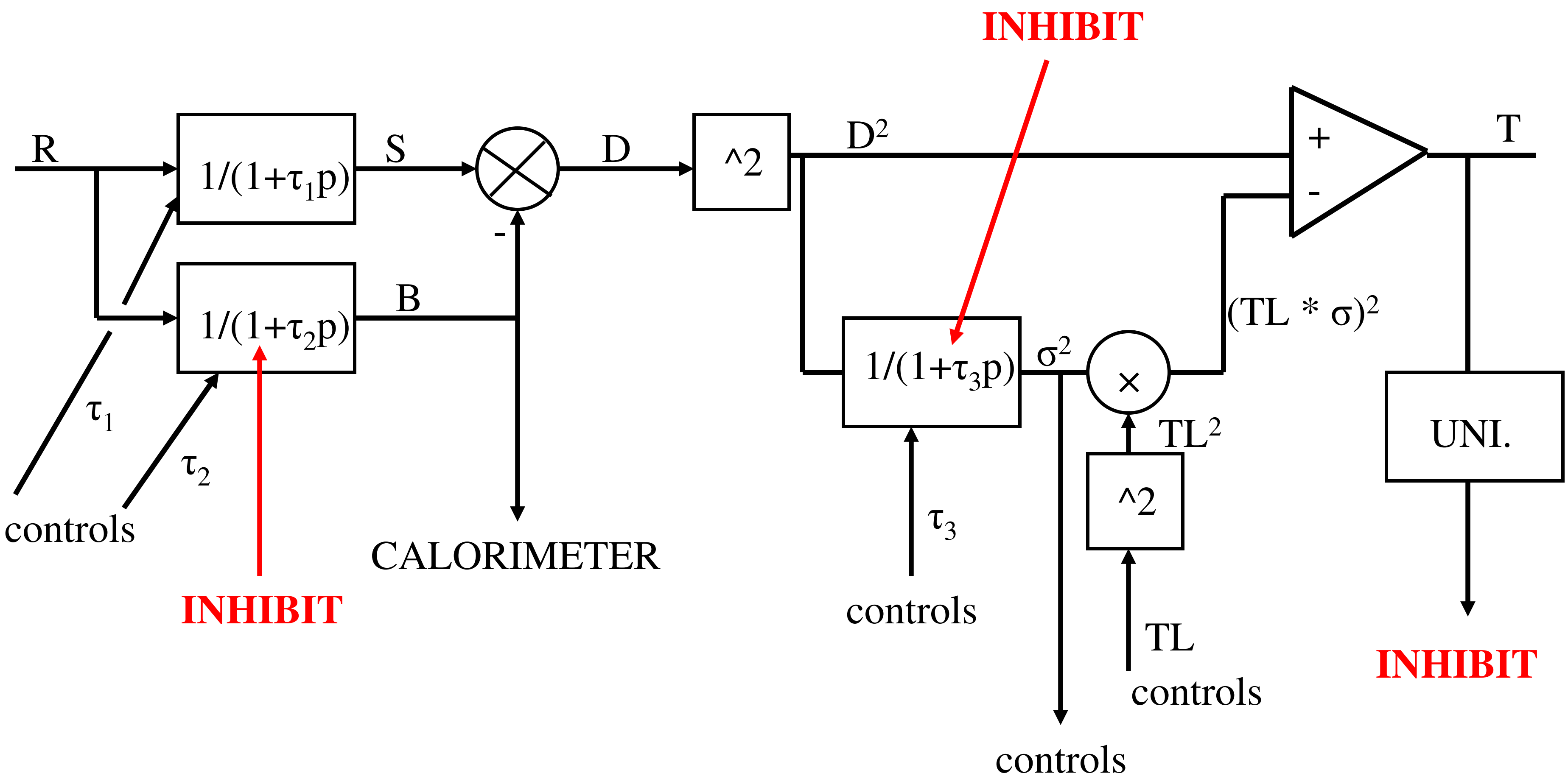
How is our *baseline follower* set up?

- dynamics:
  - → pulse P — time scale = pulse width W
  - → baseline B — time scale > W
  - → baseline noise σ^2 — time scale >> W (~ constant)

	principle	simplification
raw signal R	R_i	-
filtered raw signal S	$S_i = f(R_i, R_{i-1}, \ldots)$	average over time scale τ_1 (< W)
baseline B	average over R bimodal	average over time scale τ_2 ($\gg \tau_1$)
σ_i^2	$(S_i - B)^2$	-
$\boldsymbol{\sigma^2}$	$f(\sigma_i^2, \sigma_{i-1}^2, \ldots)$ bimodal	average over time scale τ_3 ($> > \tau_2$)

→ TRIGGER condition: $\sigma_i^2 > k^2 * \boldsymbol{\sigma^2}$

Schematic Representation of our Trigger



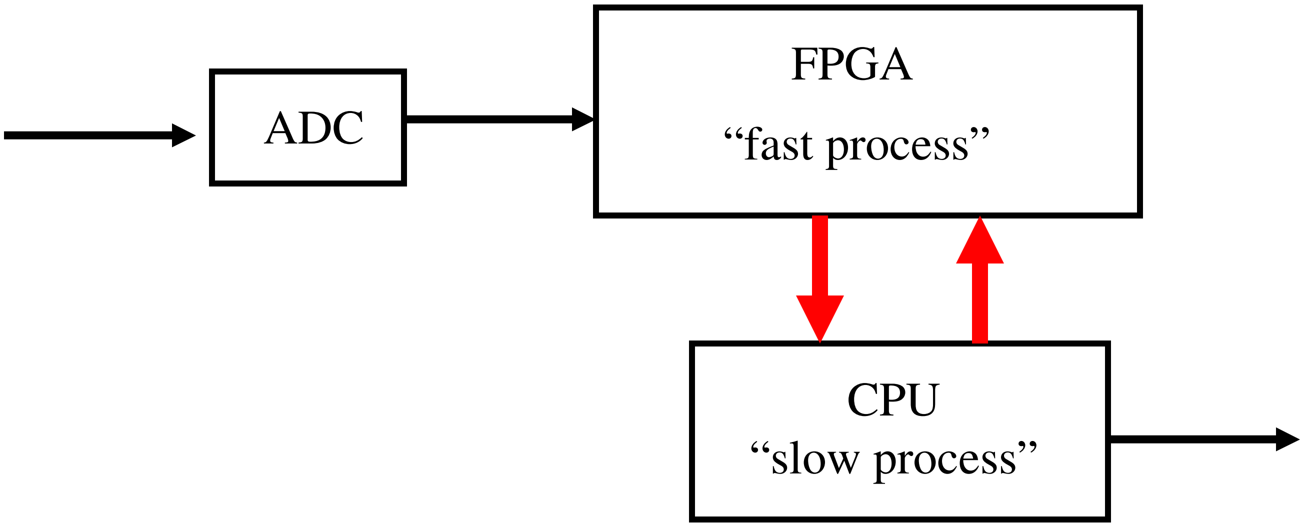
What are the *control* requirements ?

parameter	initialized to	"reasonable" value	description	communication
constant τ_1	0.5 W	"short" (< pulse width)	improves S/N BUT: introduces additional latency	R & W
constant τ_2	5 W	"long" (> pulse width)	baseline dynamics	R & W
constant τ_3	BIG	"VERY long" (>> pulse width)	baseline variance estimate	R & W

- parameters are communicated via the slow process to/ from the controls:
  - → R = read
  - → W = write
  - → A = alarm

System Learning

Interaction of the fast & the slow process



- “slow process” extracts information about pulse shape

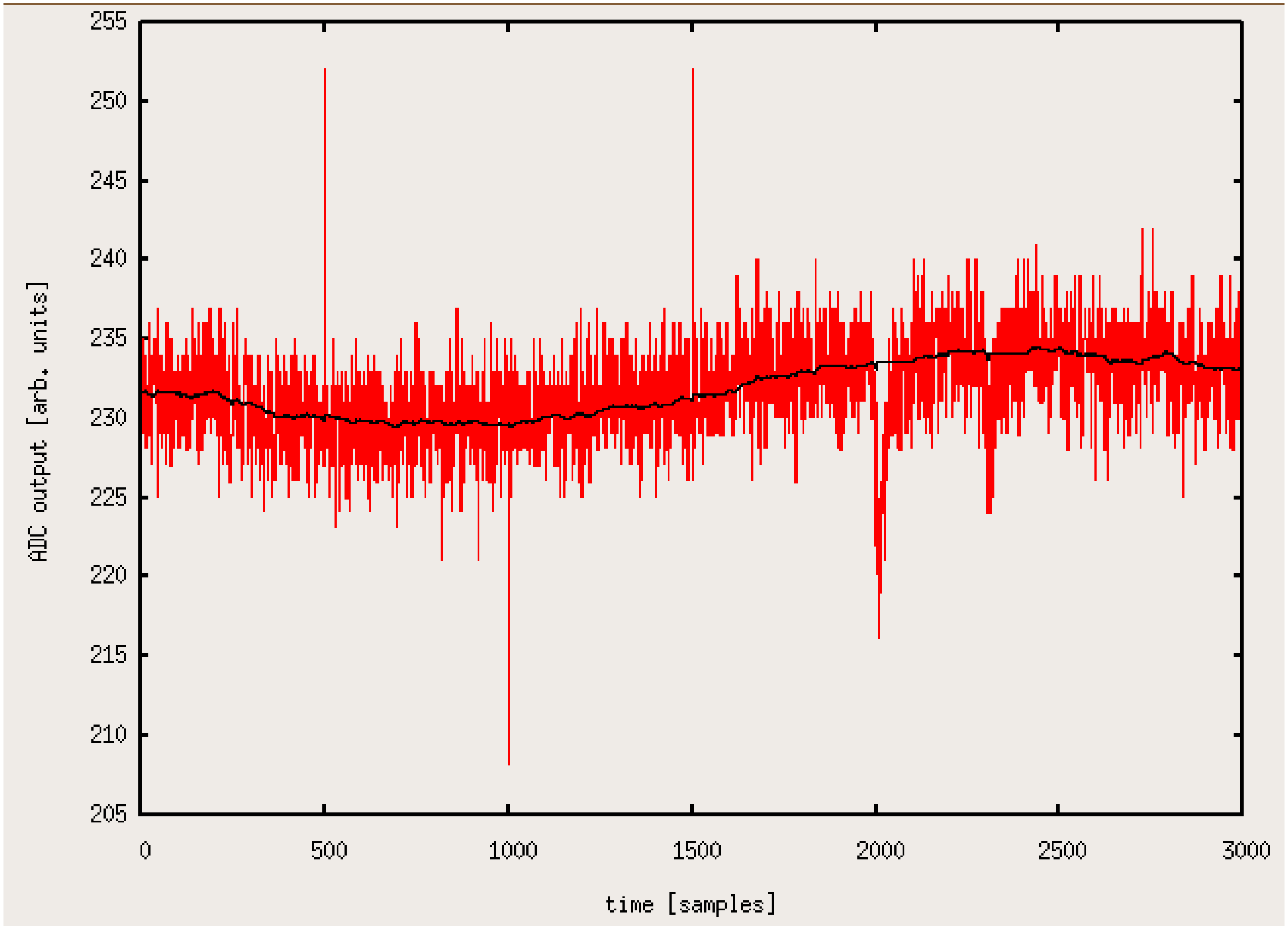
  → could send measured pulse width to “fast process” & set τ_1 and τ_2 accordingly

  → system learns

Further *control* requirements

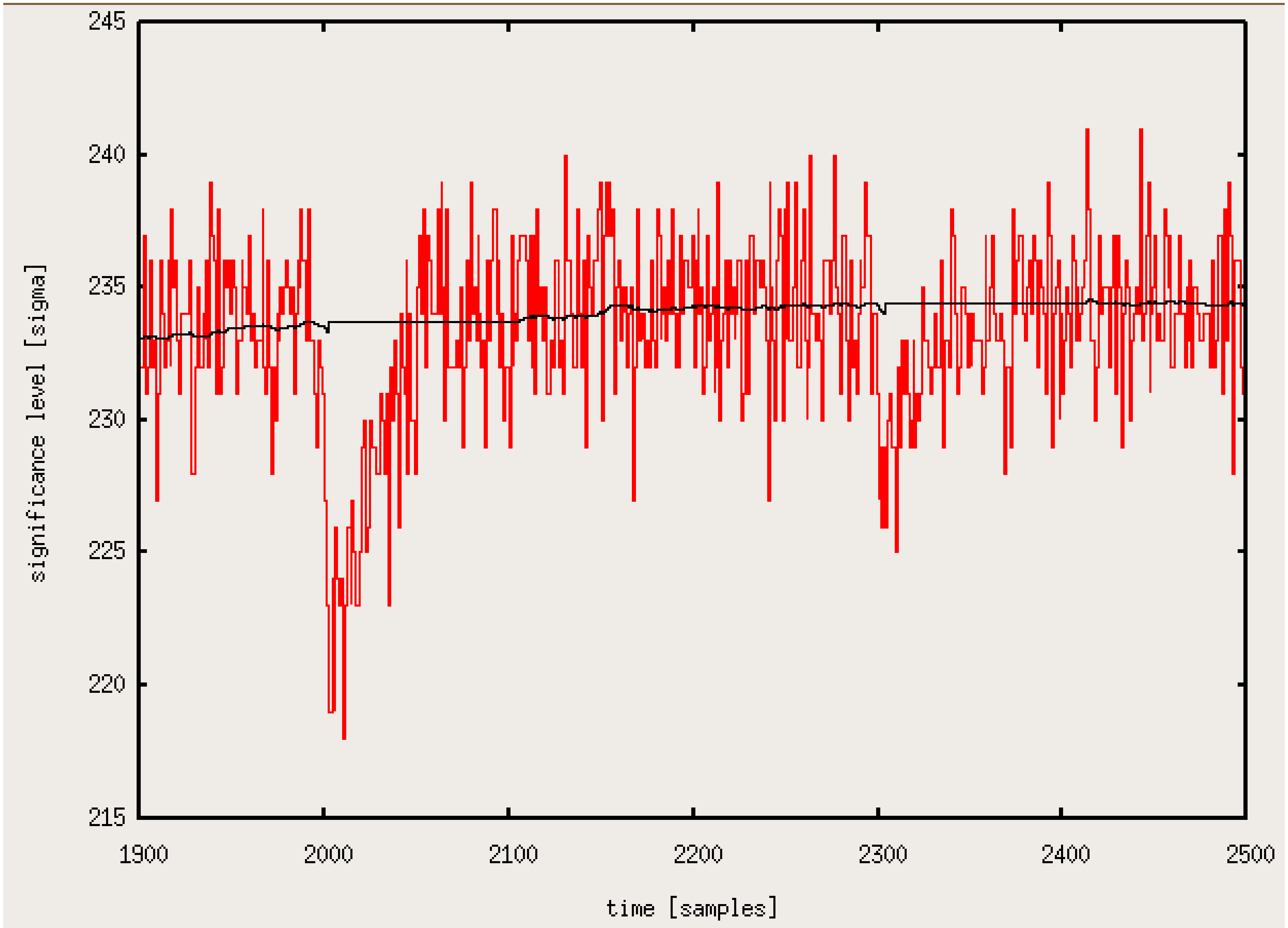
parameter	description	communication
NL	noise level → standard deviation of "pulse-less" signal (without baseline fluctuation)	R & A
TL	trigger level: expressed in units of NL → kσ-triggering	R & W
TR (optional)	triggers over last Δtime	R & A
TR Δtime (optional)	time interval of triggering	R & W
R (optional)	restart the filter	W

An Example



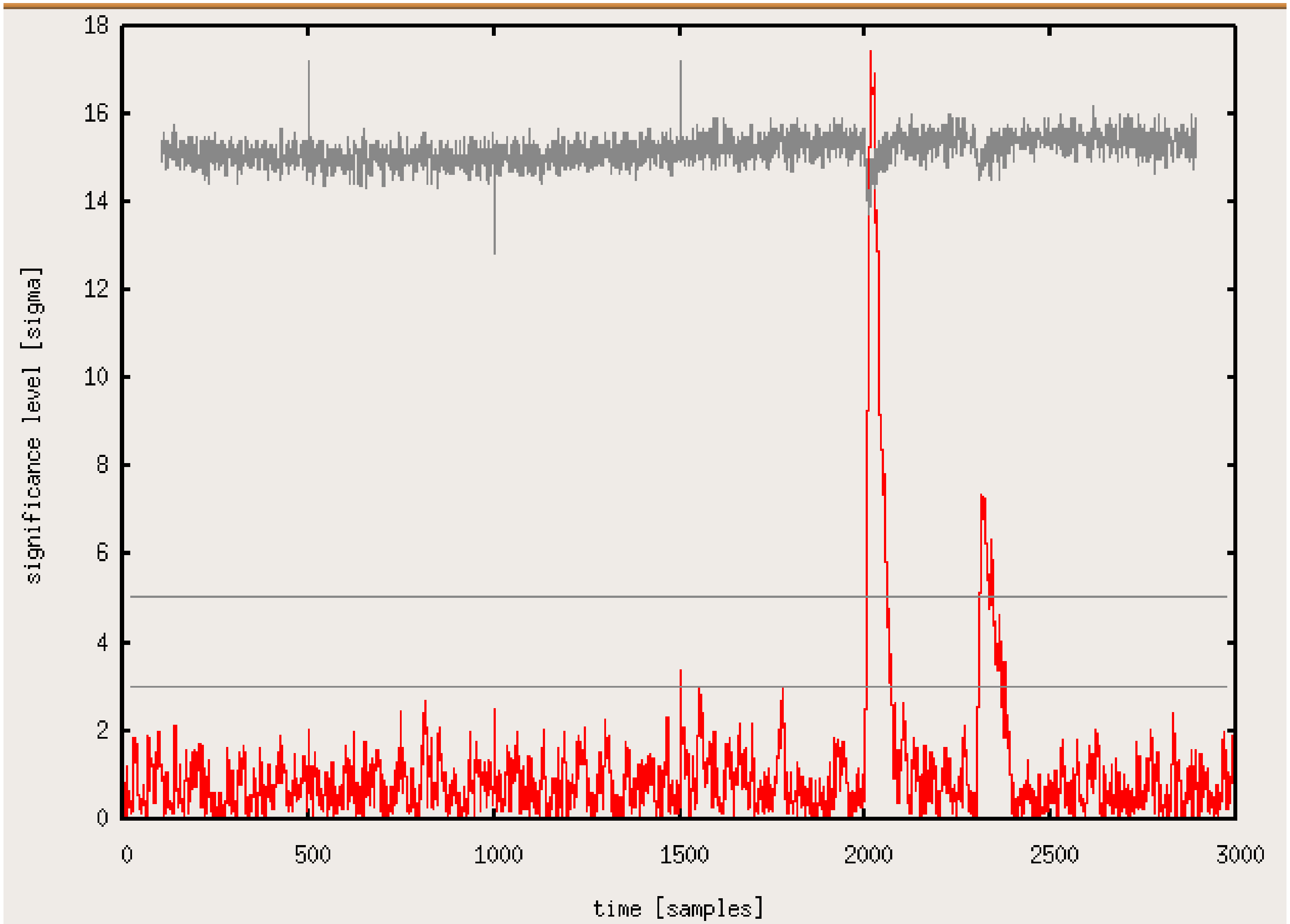
→ harmonic baseline dynamics, spikes, two “physics” pulses
→ baseline follower
→ discrete digitizer output

An Example



→ zoomed in on “physics” pulses
→ bimodal filter

An Example



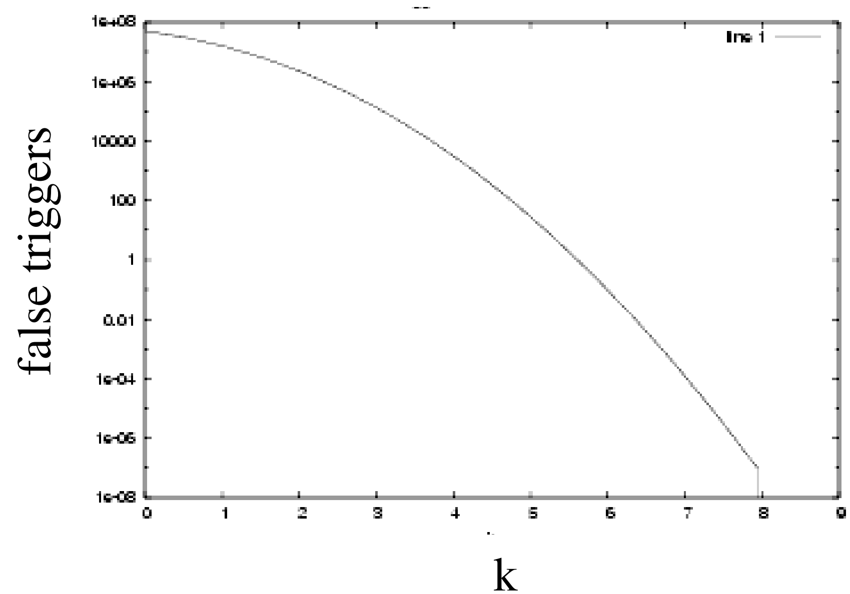
→ significance level of deviation from baseline

→ k*σ-triggering

FALSE Triggers

- false trigger rate due to random fluctuation

false trigger rate for a 100MSPS system



- reduction of false triggers due to “grouping together” of false triggers
  → neighbouring points are correlated
  → false triggers clump together
  → effectively reduces number of false triggers

- EXAMPLE:
  → 10^8 experimental data points
  → NaI crystal

  → MC simulation: 134 990 expected false triggers per second for 3σ-triggering
  → quick sample calculation: 147 800 false triggers clumped together in 79 700 “groups”
  → reduction of false trigger by ~ factor of 2

Conclusions

Bimodal Kalman filter for digital triggering:

- simplified optimal recursive baseline follower
- runs entirely in the fast process
- capable of following & reporting a dynamical baseline
- follows noise level of baseline
- higher single-point signal-to-noise ratio
- monitors “current value” of variance of baseline
- possible to define $k*\sigma$ –triggering
- successful initial test on TRBv2 board for HADES/ FAIR

VERY INTERESTING trigger for various physics applications

Thank you.