

Algorithms for identification of nearly-coincident events in calorimetric sensors

Bradley K. Alpert

Applied and Computational Mathematics Division
in collaboration with Quantum Sensors Group, NIST,
and Università di Milano-Bicocca and INFN, Italy

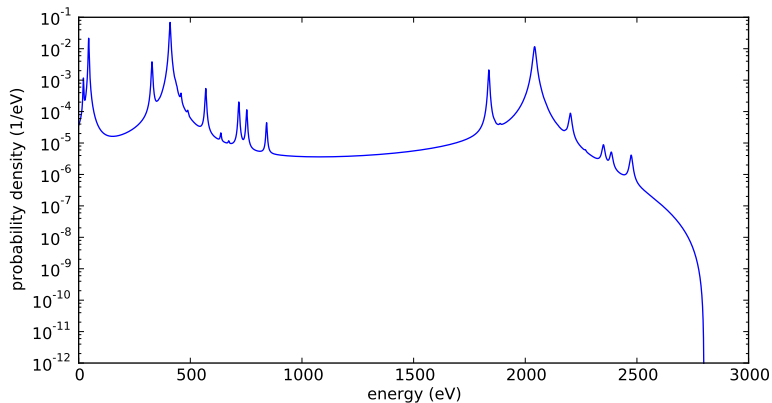


Neutrino Mass from ^{163}Ho Electron-Capture Events

^{163}Dy de-excitation spectrum endpoint $Q = 2.8$ keV increases the challenge (relative to $Q = 2.5$ keV)

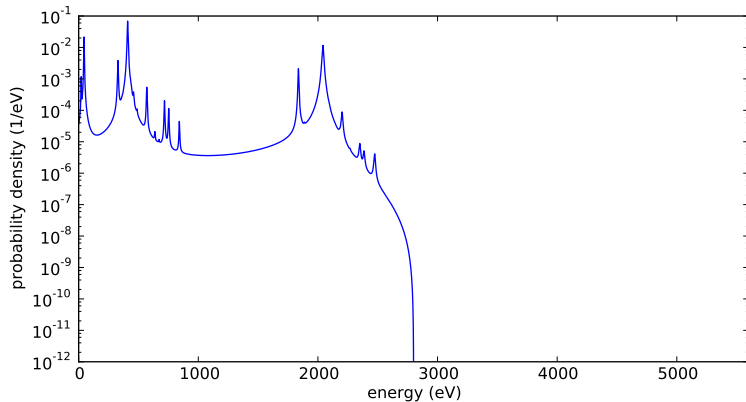
- HOLMES target event rate: 300 / s / detector
- Yields 2×10^{-4} / s / detector, energy interval [2.70, 2.82] keV
- Energies near Q dominated by pile-ups over single events
- Detection and rejection of most pile-ups crucial for experiment

^{163}Dy De-Excitation Energy Spectrum



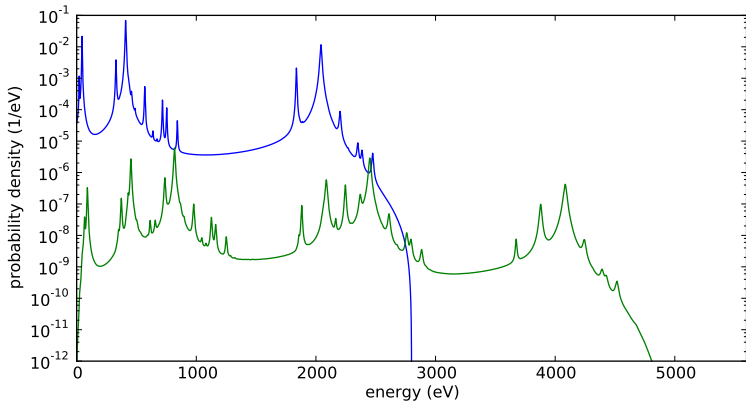
Based on one- and two-hole states

^{163}Dy De-Excitation Energy Spectrum



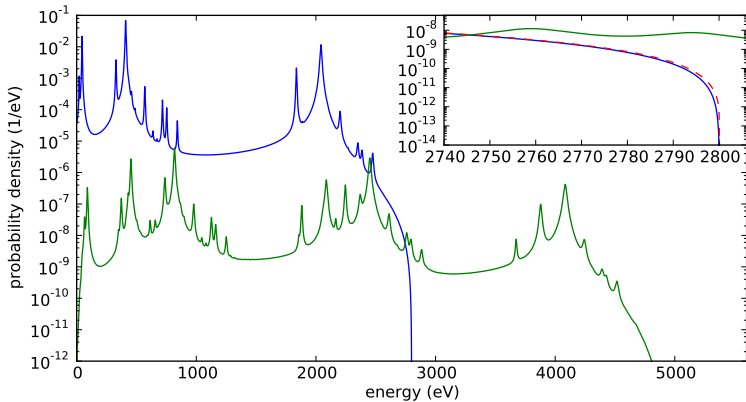
Rescaled energy axis

^{163}Dy De-Excitation Energy Spectrum



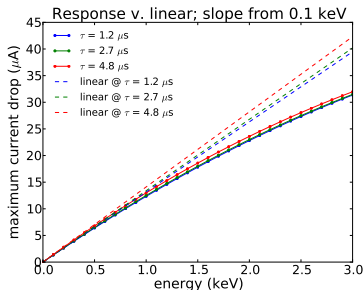
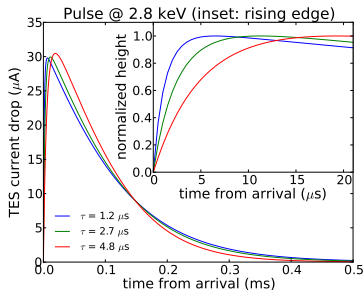
Pile-up (self-convolution) spectrum scaled for 1 μs time resolution

^{163}Dy De-Excitation Energy Spectrum



Inset: energies near Q with $m(\nu_e) = 0.0$ eV (blue), 1.0 eV (red)

Detector Dynamics and Noise Model for Simulation



Irwin-Hilton (2005) TES noise model and detector dynamics model

$$C \frac{dT}{dt} = -k \cdot (T^n - T_{\text{bath}}^n) + I^2 R(T, I) + \sum_i \delta(t - t_i) \cdot E_i$$

$$L \frac{dI}{dt} = V - I \cdot R_L - I \cdot R(T, I)$$

enhanced with Shank et al. (2014) model for transition resistance

$$R(T, I) = \frac{R_N}{2} \left[1 + \tanh \left(\frac{T - T_c + (I/A)^{2/3}}{2 \ln(2) T_w} \right) \right].$$

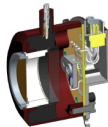
Neutrino Mass from ^{163}Ho Electron-Capture Events

Construction of model—from noisy data—for single-pulse records

1 Training data: separate single- from double-pulse records

- Propose increased single-pulse count near Q with *switchable* source: $L\alpha$ x-ray lines of Ru (2.688 keV), Pd (2.839 keV)
- Detect pile-ups as outliers, with SVD

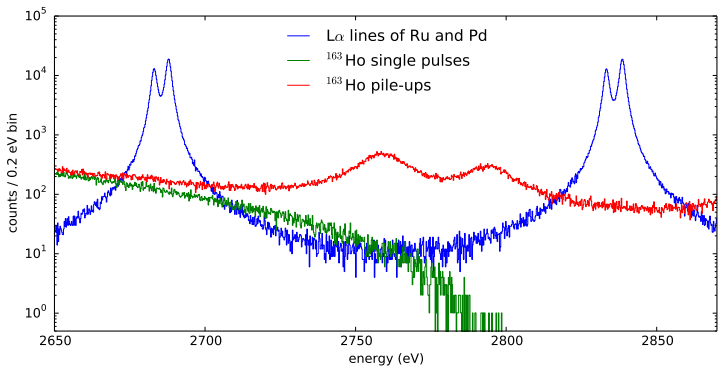
C. deVries et al. (2012), “Calibration sources ... ASTRO-H”:



2 Use singular value decomposition (SVD) to build model of single-pulse records

- Pre-trigger mean, pulse amplitude, pulse arrival time are independent factors; latter two extracted as singular vectors
- Simulations neglect additional factors, such as rising-edge readout distortions

Training Data with Switchable Source



- Less than 1 Ru, Pd x-ray photon / s / detector
- Strong majority of records contain single pulses, before,
- and almost all single pulses, after outlier detection

Training Data: Processing to Remove Outliers

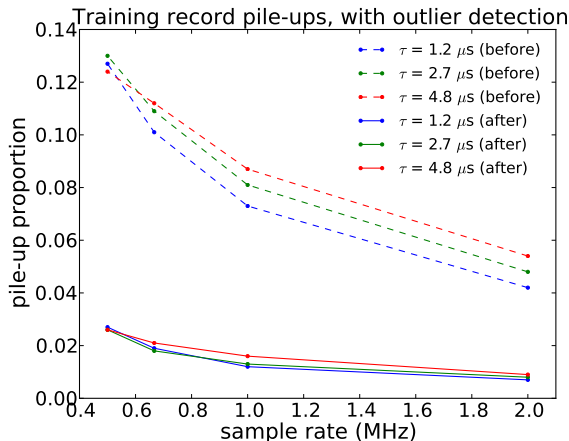
Iterate

- Form matrix M : columns are noise-whitened pulse records
- Compute SVD $M = UDV^t$, retaining first $j = 6$ columns of U
- Subtract means of first j columns of V , obtaining \hat{V}
- Empirical covariance $\hat{\sigma}^2 = \hat{V}^t \hat{V}$ computed
- Compute squared deviation $d_i^2 = \hat{V}_{i,:} (\hat{\sigma}^2)^{-1} \hat{V}_{i,:}^t$, each record
- Discard records with largest d_i^2

three times, discarding 1/2, 1/4, 1/8 expected number of pile-ups

Single-pulse records now predominate

Training Data with Switchable Source



- Less pile-up at higher sample rates, and
- Less pile-up with faster pulse rise, but
- After outlier detection these differences are largely reduced

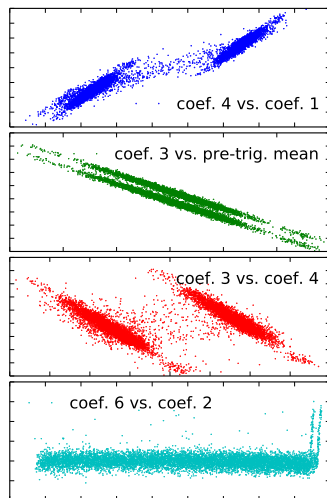
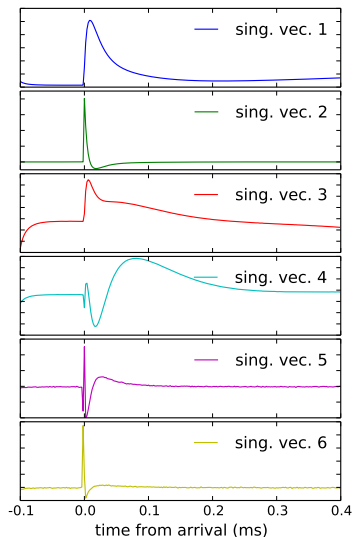
Building Model of Single-Pulse Records

- Again M : columns are noise-whitened culled training records
- Compute SVD $M = UDV^t$, retaining first $j = 6$ columns of U
- First j expansion coefficients $(VD)_{i,:}$: for record i combined with pre-trigger mean
- First column of U approximates the average pulse, while second is dominated by the effect of arrival time on pulse shape
- Remaining $j - 2$ basis vectors encode variations due to changing baseline and nonlinear effects of varying pulse height

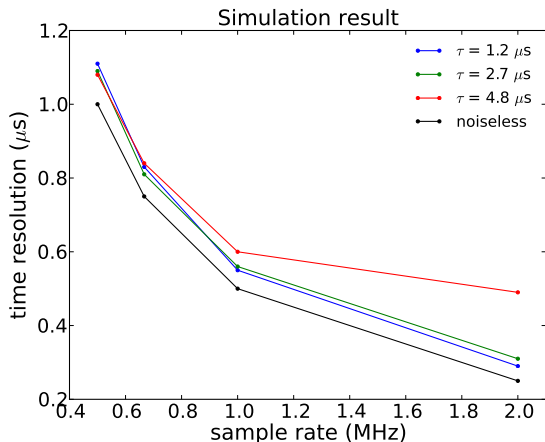
We approximate coefficients $3, \dots, j$ by linear regression from $1, x, y, z, xy, yz, zx, xyz$, where x, y, z denote the pre-trigger mean and the first two coefficients.

From the regression coefficients, residual for any record is obtained.

Pulse Record Singular Vectors and Coefficients

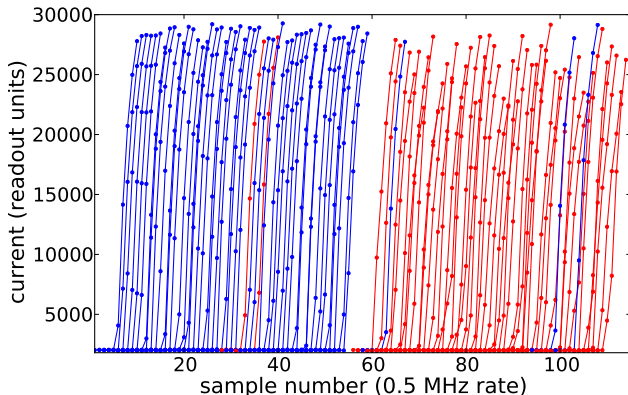


Performance of Pile-Up Detection



- Simulation's pile-up detection close to optimal—noiseless case—determined by sample rate
- Pulse rise time (i.e., detector inductance) has minor effect

Example of Classifier Performance



For 0.5 MHz sample rate and $\tau = 4.8 \mu\text{s}$, 5 pre- and post-trigger samples of 50 single-pulse records (left) and 50 piled-up records (right), classified as single-pulse (blue) or as piled-up (red).

Cost of Pile-Up Detection

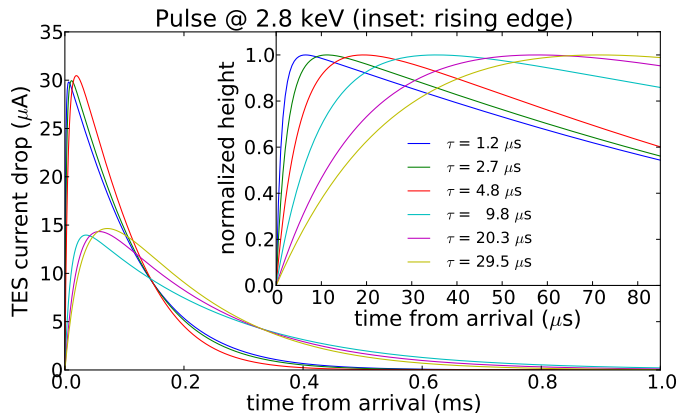
Cost of detection dominated by $j = 6$ inner products of singular vectors with pulse records

Comparable in cost to optimal filtering: 5 inner products with translates of optimal filter

Preliminary Detector Fabrication

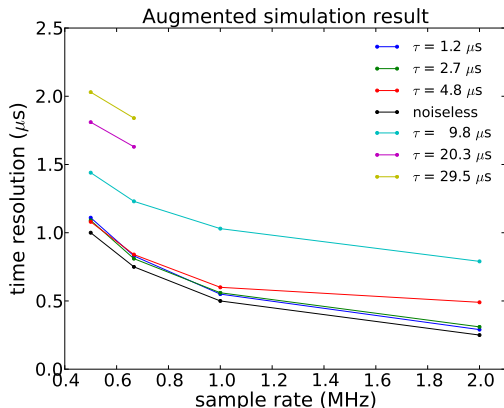
- Foregoing simulations were based on response of modeled detector with anticipated parameter choices
- Newer understanding, including changes in detector-absorber layout, multiplexing, and readout, have shifted detector parameter choices toward slower rise and longer duration pulses
- Does time resolution remain insensitive to these effects?

Old and New Detector Models



- Pulse durations roughly double
- Rise times roughly quadruple
- Latter causes deterioration in time resolution

Performance of Pile-Up Detection: Augmented



- Longer pulse rise times have larger effect on time resolution than shorter rise times simulated initially
- Loss of significance of sub-sample arrival time, for fast sampling rates and slow pulse rises, reveals detection procedure limitation

Summary

New algorithms

- Separate minority of pile-ups in training data as outliers
- Build single-pulse model by regression of SVD coefficients

Developed for TES microcalorimeters, but not limited to them

Simulations show

- Near-optimal time resolution, determined by sample rate, for fairly rapid pulse rises, but
- Time resolution deteriorates with relatively long pulse rise times