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Artificial neural network-based method for discriminating Compton scattering events in high-purity germanium γ-ray spectrometer

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Abstract

To detect radioactive substances with low activity levels, an anticoincidence detector and a high-purity germanium (HPGe) detector are typically used simultaneously to suppress Compton scattering background, thereby resulting in an extremely low detection limit and improving the measurement accuracy. However, the complex and expensive hardware required does not facilitate the application or promotion of this method. Thus, a method is proposed in this study to discriminate the digital waveform of pulse signals output using an HPGe detector, whereby Compton scattering background is suppressed and a low minimum detectable activity (MDA) is achieved without using an expensive and complex anticoincidence detector and device. The electric-field-strength and energy-deposition distributions of the detector are simulated to determine the relationship between pulse shape and energy-deposition location, as well as the characteristics of energy-deposition distributions for full- and partial-energy deposition events. This relationship is used to develop a pulse-shape-discrimination algorithm based on an artificial neural network for pulse-feature identification. To accurately determine the relationship between the deposited energy of gamma rays in the detector and the deposition location, we extract four shape parameters from the pulse signals output by the detector. Machine learning is used to input the four shape parameters into the detector. Subsequently, the pulse signals are identified and classified to discriminate between partial- and full-energy deposition events. Some partial-energy deposition events are removed to suppress Compton scattering. The proposed method effectively decreases the MDA of an HPGe γ-energy dispersive spectrometer. Test results show that the Compton suppression factors for energy spectra obtained from measurements on 152Eu, 137Cs, and 60Co radioactive sources are 1.13 (344 keV), 1.11 (662 keV), and 1.08 (1332 keV), respectively, and that the corresponding MDAs are 1.4%, 5.3%, and 21.6% lower, respectively

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Preamble

Artificial Neural Network-Based Method for Discriminating Compton Scattering Events in High-Purity Germanium γ-Ray Spectrometers

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Abstract: To detect radioactive substances with low activity levels, anticoincidence detectors are typically used alongside high-purity germanium (HPGe) detectors to suppress Compton scattering background, thereby achieving extremely low detection limits and improved measurement accuracy. However, the required hardware is complex and expensive, limiting the method's broader application. This study proposes an alternative approach that discriminates digital pulse waveforms from an HPGe detector to suppress Compton scattering background and achieve low minimum detectable activity (MDA) without requiring costly anticoincidence systems. We simulated the electric-field strength and energy-deposition distributions within the detector to establish the relationship between pulse shape and energy-deposition location, as well as the characteristic distributions for full- and partial-energy deposition events. This relationship enabled development of a pulse-shape-discrimination algorithm based on artificial neural networks for pulse-feature identification. To accurately characterize how deposited γ-ray energy relates to deposition location, we extracted four shape parameters from the detector's output pulse signals. These parameters were then used as inputs for machine learning-based classification to discriminate between partial- and full-energy deposition events, allowing suppression of Compton scattering by removing some partial-energy deposition events. The proposed method effectively reduces the MDA of HPGe γ-energy dispersive spectrometers. Test results demonstrate that the Compton suppression factors for energy spectra from 152Eu, 137Cs, and 60Co radioactive sources are 1.13 (344 keV), 1.11 (662 keV), and 1.08 (1332 keV), respectively, with corresponding MDA reductions of 1.4%, 5.3%, and 21.6%.

Keywords: High-purity germanium γ-ray spectrometer; Pulse-shape discrimination; Compton scattering; Artificial neural network; Minimum detectable activity

1. Introduction

Incomplete deposition of gamma-ray energy in a detector increases the Compton background count in γ-ray spectra and reduces the peak-to-Compton ratio, which adversely affects both qualitative and quantitative spectral analysis. The anticoincidence technique is commonly employed for Compton suppression, but requires one or more anticoincidence detectors with electronic circuits, increasing system volume, complexity, and maintenance costs. Pulse-shape discrimination (PSD) offers an alternative approach that can suppress Compton scattering background without anticoincidence detectors or complex electronics. PSD-based instruments are simpler to design and manufacture, offer lower maintenance, higher reliability, and reduced costs, making them attractive for both portable and laboratory radiation detection applications. Consequently, PSD methods are increasingly being adopted for background Compton scattering suppression.

Classical PSD methods—including those based on the ratio of maximal current signal amplitude to event energy (A/E), analysis of current waveform trailing edges, and charge waveform rise-time ratios—can suppress background by distinguishing single- from multi-point events, thereby enhancing the peak-to-Compton ratio. However, such background suppression typically comes at the cost of reduced full-energy peak counts. Reducing the minimum detectable activity (MDA) requires accurate event-type screening to subtract background with minimal or no loss of full-energy peak counts. Simulation and experimental studies reveal that preamplifier output pulse shapes depend not only on single- versus multi-point events but also significantly on energy-deposition location within the detector. This location dependence affects event-type identification accuracy. In detector low-energy regions where photoelectric interactions dominate, conventional PSD removal of single-point events increasingly eliminates full-energy deposition events. Consequently, PSD applied to HPGe systems has shown limited success for background suppression in low-energy regions. Furthermore, pulse waveforms reflect multiple physical factors—including interaction type and energy-deposition location—introducing considerable complexity. Incorporating multiple waveform features can provide more detailed shape characterization and more effective information for event-type identification, thereby improving discrimination accuracy.

This study determines the relationship between pulse shape and energy-deposition location and uses this location information for event-type discrimination. We introduce a multiparameter approach to provide more effective identification information and employ an artificial neural network to screen event types. This combination improves event-type identification accuracy, enhances the peak-to-Compton ratio, and reduces MDA by significantly suppressing Compton scattering background counts while preserving most full-energy peak counts.

2.1 Detector modeling

We used SolidStateDetectors.jl [34] to model and simulate an HPGe detector for investigating the relationship between pulse shape and energy-deposition location. The coaxial HPGe detector had a diameter of 63.6 mm, height of

59.8 mm, electrode diameter of 7.5 mm, and electrode height of 43.5 mm. Its three-dimensional structure is shown in Figure 1 [Figure 1: see original paper]. The anode potential, cathode potential, and bias voltage were set to 0, -2200, and 2200 V, respectively. The operating temperature was 78 K. The simulation configured a cylindrical impurity concentration distribution model that varied radially and vertically, with a central concentration of 5.8×10^9 atoms $\cdot$ cm^{-3} and an edge concentration of ~6.2×10^9 atoms $\cdot$ cm^{-3}.

2.1 Field-Strength Simulation

Electric field $\vec{E}$ is one of two components required to calculate charge-carrier drift trajectories. Calculating the electric field requires solving the Poisson equation for electric potential $\phi(r)$:

$$\nabla^2\phi(r) = -\frac{\rho(r)}{\varepsilon_0\varepsilon_r} \quad (1)$$

where $\rho(r)$ represents spatial charge density, ε_0 the dielectric constant, and ε_r the dielectric distribution.

The electric field $\vec{E}$ is calculated as:

$$\nabla\vec{E} = \frac{\rho(r)}{\varepsilon_0\varepsilon_r}$$

The open-source package SolidStateDetectors.jl solves for electric potential and field strength in each detector grid using the successive over-relaxation (SOR) algorithm. It computes and visualizes these distributions, generating contour plots of equipotential and electric-field lines, as shown in Figure 2 [Figure 2: see original paper].

To calculate the germanium crystal's weighting potential distribution and determine electrode signals during charge-carrier drift, we solved for weighting potential $\phi(r)$ using the Poisson equation with boundary conditions. The anode and cathode weighting potentials were assumed to be 1 and 0 V, respectively:

$$\phi(r) = \begin{cases} 0\,\mathrm{V} & \forall r \in C_{\mathrm{uncol}} \\ 1\,\mathrm{V} & \forall r \in C_{\mathrm{col}} \end{cases}$$

where C_{col} represents the collecting electrode and C_{uncol} the non-collecting electrode. By setting space charge to zero and performing multiple SOR iterations, we obtained the weighting-potential distribution shown in Figure 3 [Figure 3: see original paper].

2.3 Drift-velocity model

The relationship between drift velocity vector v and electric field vector $\vec{E}$ is:

$$v_{e/h} = \mu_{e/h}(\vec{E})\vec{E}(r) \quad (4)$$

where $v_{e/h}$ is the drift velocity of charge carriers (with e and h denoting electrons and holes, respectively) and $\mu_{e/h}$ represents carrier mobility.

Due to Ge crystal band structure, conductivity becomes anisotropic at high electric fields and low temperatures. This anisotropy yields different carrier drift velocities along different crystal axes. When the electric field direction is not aligned with the crystal's rotational symmetry axis, the drift velocity develops a nonzero angle relative to the applied field. Drift velocities along the $\langle 100 \rangle$, $\langle 110 \rangle$, and $\langle 111 \rangle$ crystal axes are described by [35-37]:

$$v_{e/h} = \frac{\mu_0 \vec{E}}{(1 + (|\vec{E}|/E_0)^{\beta})} - \mu_n \vec{E} \quad (5)$$

where scalar μ_0 is low-field mobility, $\vec{E}$ is electric field strength, and E_0, β, and μ_n are adjustment parameters.

At low field strengths (0.1 kV/cm $\leq$ E $\leq$ 3 kV/cm), the Gunn effect is negligible and mobility becomes isotropic. The mobility fitting parameter μ_0 is orientation-independent, simplifying the velocity formula to Equation (4). However, when E $\geq$ 3 kV/cm, the Gunn effect becomes significant, requiring the $\mu_n \vec{E}$ correction term. The AGATA collaboration determined empirical parameter values for drift velocity under experimental conditions, listed in Table 1 [36][37]. These parameters can be configured in ADLChargeDriftModel, enabling SolidStateDetectors.jl to accurately simulate carrier migration velocities.

2.4 Waveform simulations

Waveform simulations calculated carrier drift velocities throughout the detector based on electric-field distributions and drift-velocity models. We specified initial carrier positions and time steps, computed drift trajectories, and combined these with weighting potentials via the Shockley–Ramo theorem to calculate induced electrode charges, which were then converted to voltage pulse waveforms. During simulation, charge carriers were treated as ideal point charges.

Based on the Ge crystal's weighting potential distribution and carrier drift velocities, the Shockley–Ramo theorem calculates signal waveforms induced on the readout electrode by drifting carriers [38]. For an electron–hole pair created at point r with equal and opposite static charge q, with electron and hole drift trajectories r_e and r_h, the induced charge $Q(t)$ at time t is:

$$Q(t) = -q\{\phi[r_h(t)] - \phi[r_e(t)]\} \quad (6)$$

where ϕ represents the weighting potential at carrier positions.

Simulated waveform amplitudes are expressed in units of charge e_0. In a charge-sensitive preamplifier, induced charges integrate onto the feedback capacitor and convert to voltage signals while continuous discharge occurs through the feedback resistor. The preamplifier output voltage $U_{\text{out}}(t)$ is:

$$U_{\text{out}}(t) \approx \frac{Q(t) \cdot e_0}{C_f} \cdot \frac{\tau}{t} \quad (7)$$

where $e_0 = 1.6 \times 10^{-19}$ C is the elementary charge, C_f the feedback capacitance, and τ the time constant. In our system, $C_f \approx 0.1$ pF and $\tau = 85$ µs. With pulse rise times under 400 ns, τ is effectively constant, allowing us to neglect front-edge voltage loss from feedback resistor discharge. The preamplifier output voltage simplifies to:

$$U_{\text{out}}(t) = Q(t) \cdot e_0 \quad (8)$$

We simulated and analyzed waveforms at multiple axial and radial positions. Along the cylindrical axis, initial carrier heights were set from 44.5 to 59.5 mm in 1 mm steps, yielding 16 waveforms (Figure 4 Figure 4: see original paper). At 25 mm axial height, radial positions varied from 4.5 to 30.5 mm in 2 mm steps, producing 14 waveforms (Figure 4(b)). Three representative waveforms from each direction illustrate shape differences (Figures 4(c) and 4(d)). Energy-deposition location significantly affects pulse-waveform shape in both directions. Near-cathode deposition produces fast-to-slow rise times, near-anode deposition yields slow-to-fast rise times, and intermediate-depth deposition creates fast-to-slow-to-fast rise times with a reverse "S" shape.

2.5 Analysis of charge-cloud effect

Charge-carrier motion is not governed solely by external electric fields; diffusion and self-repulsion significantly influence drift. To model this, we represent electrons and holes not as single point charges but as charge clouds composed of multiple point charges. This approach incorporates both diffusion (random thermal motion) and self-repulsion (repulsive interactions between like carriers) while neglecting electron-hole attraction.

SolidStateDetectors.jl offers two charge distribution options. For clouds with fewer than 50 charges, a Platonic polyhedron shell distributes point charges on its vertices. For clouds exceeding 50 charges, point charges distribute uniformly on a spherical surface.

The number of carriers generated by energy deposition in high-purity Ge is:

$$n = \frac{E}{\omega} \quad (9)$$

where n is the number of carriers, E the deposited energy, and ω the ionization energy. At liquid nitrogen temperature (77 K), high-purity Ge's average ionization energy is ~3 eV. For deposition energies of 344, 662, and 1332 keV, Equation (9) yields approximately 114,667, 220,667, and 444,000 carriers, respectively. Consequently, we used the spherical surface uniform distribution model, setting the NBodyChargeCloud function's total charge parameter to these values.

Figure 5 Figure 5: see original paper compares electrode charge-pulse waveforms from cloud-charge and point-charge models for 662 keV deposition at Z = 58.5 mm (1.3 mm from the top anode). As electrons drift toward the anode, those nearest reach it first, while holes drifting toward the cathode arrive later due to greater initial distance. The point-charge model treats all electrons as arriving simultaneously, causing rapid signal increase. The charge-cloud model distributes electrons spherically, so boundary electrons arrive first, followed by central electrons, then far-boundary electrons. This gradual electron arrival produces slower anode charge induction than the point-charge model. Subtracting the two waveforms yields the first pulse in Figure 5(b). Hole drift toward the cathode produces a similar second pulse. Due to holes' slower drift velocity, the charge-cloud model's induced charge amplitude changes more slowly than for electrons, resulting in larger post-subtraction pulse amplitudes for holes.

Thus, different models produce slight differences in carrier spatial distribution, causing minor variations in induced charge waveforms during electrode drift.

We quantified these differences by simulating both models at 344, 662, and 1332 keV deposition energies along the axis from z = 44.5 to 58.5 mm in 1 mm steps. After calculating waveforms for both models and extracting maximum charge differences, we plotted the results in Figure 6 Figure 6: see original paper. Position changes did not affect maximum charge differences, but increasing deposition energy increased differences under both models because higher carrier counts expand charge cloud radius and density. Larger radius increases acquisition time, while higher density increases total charge, amplifying inter-model differences during acquisition.

Figure 6(b) shows maximum relative error as a measure of the charge-cloud model's waveform impact. Relative error remained below 5% from z = 45.5 to 57.5 mm. Near electrodes, error increased because rapid cloud acquisition produced lower waveform values at maximum difference, yielding larger relative errors when these small values served as denominators. Nevertheless, all relative errors stayed below 10%, indicating the charge-cloud model's effect on waveform shape is negligible.

2.6 Simulation of energy-deposition location

We examined two event types: full- and partial-energy deposition. This section establishes the relationship between energy-deposition location and event type, enabling discrimination based on deposition location distribution differences. Using the GEometry ANd Tracking (GEANT4) package [39-41] from CERN, we simulated interactions of 344-, 662-, and 1332-keV γ-rays from 152Eu, 137Cs, and 60Co sources in a coaxial HPGe detector [42]. The GEANT4 environment used the QBBC physics list, incorporating the G4EM standard electromagnetic package and G4DecayPhysics package. Our detector model replicated a laboratory N-type coaxial HPGe detector with 63.3 mm diameter and 59.8 mm height Ge crystal, a 0.6-mm-thick aluminum sheet 6.3 mm above the crystal (simulating the detector shell), and a 300-nm borided layer as a thin top window. Figure 7 Figure 7: see original paper shows the crystal and aluminum shell dimensions and positions.

The radiation source was a 63.3-mm-diameter circular planar source centered on the detector axis, positioned 40 mm above the detector surface. We simulated 200,000 γ-rays at each energy, emitted along the negative z-axis (Figure 7(b)). In GEANT4, γ-rays first passed through the aluminum casing and window before interacting with the Ge crystal. We statistically analyzed transport processes, reaction types, and step-level interaction points within the crystal. Event selection and coordinate extraction were performed using the SteppingAction.cc program file. Selection criteria were:

Partial-energy deposition events: Previous energy deposition occurred within the Ge crystal, subsequent radiation crossed the Ge-medium boundary, and the crossing radiation's kinetic energy exceeded 0.

Full-energy deposition events: Previous energy deposition occurred within the Ge crystal, and subsequent radiation's kinetic energy was 0.

Post-simulation, we recorded incident ray counts, total energy-deposition events, and full- and partial-energy deposition event counts (Table 2). Processing event coordinates into radii and heights yielded interaction position distributions for both event types (Figure 8 [Figure 8: see original paper]).

Results show full-energy deposition events occur primarily deep in the detector, while partial-energy deposition events concentrate near the surface. Thus, event type can be identified from γ-ray energy deposition location.

This analysis reveals the interconnections among pulse shape, energy-deposition location, and event type, along with their underlying mechanisms.

3. Data-processing algorithm

Combining PSD with machine learning enables more accurate event identification. We developed a PSD algorithm based on artificial neural network (ANN) pulse-feature recognition using four leading-edge waveform features as decision parameters. These features provide effective event-type identification information. Since features contribute differently to identification (i.e., have different weights) and manual weight assignment is challenging, we employed machine learning to train the ANN. The training algorithm continuously optimizes network weights, with the optimal model achieving highest event-type discrimination accuracy and best Compton scattering suppression performance. Training comprises three stages: (1) determining the leading edge's effective range from pulse signals, (2) extracting four decision parameters from this range using the PSD algorithm, and (3) constructing the ANN model and dataset.

3.1 Data stripping

γ-ray energy deposition creates electron–hole pairs that drift under electric fields, manifesting in the charge-sensitive preamplifier's rising phase. We extracted leading-edge waveforms for analysis. Each leading edge contains N_{Total} sampling points, which we preprocessed before PSD analysis.

Pulse leading-edge amplitude P_{AMP} is calculated as peak amplitude P_{PEAK} minus baseline P_{BASE}:

$$P_{\text{AMP}} = P_{\text{PEAK}} - P_{\text{BASE}} \quad (10)$$

To reduce noise interference and prevent amplitude time-walk [43], we extracted a prescribed percentage of the leading-edge amplitude to define an effective signal range. Dynamic upper (TH_{UP}) and lower (TH_{LW}) limits were:

$$TH_{\text{UP}} = r_{\text{UP}} \cdot P_{\text{AMP}} + P_{\text{BASE}} \quad (11)$$

$$TH_{\text{LW}} = r_{\text{LW}} \cdot P_{\text{AMP}} + P_{\text{BASE}} \quad (12)$$

where r_{UP} and r_{LW} are upper and lower amplitude percentages. We set $r_{\text{UP}} = 90\%$ and $r_{\text{LW}} = 10\%$ to calculate dynamic thresholds, yielding the effective range shown in Figure 9 [Figure 9: see original paper]. Digital signal gain was approximately 12.6 LSB/keV (LSB = ADC least significant bit).

For small-amplitude signals, baseline noise may trigger the lower threshold before the signal leading edge (Figure 9(b)). To prevent false triggers, we used reverse sampling to capture the lower threshold trigger index and normal sampling for the upper threshold. Trigger indices must satisfy:

$$P[M'-1] > TH_{\text{LW}} \text{ and } P[M'] < TH_{\text{LW}} \quad (13)$$

$$P[N] < TH_{\text{UP}} \text{ and } P[N+1] > TH_{\text{UP}} \quad (14)$$

where $P[n]$ is the leading-edge waveform, M' is the reverse-sampling index where the sample first falls below the lower threshold, and N is the forward-sampling index where the sample first falls below the upper threshold. M' converts to forward index M via:

$$M = N_{\text{Total}} - M' \quad (15)$$

After obtaining indices M and N, the effective-range waveform $w[n]$ is:

$$w[n] = P[M + n - 1] - P[M], \quad n = 1, 2, \dots, N - M + 1 \quad (16)$$

3.2 Feature extraction

The PSD algorithm proceeds as follows: First, calculate the effective signal's slope (extracted above). Then subtract this slope from each discrete amplitude within the effective interval to generate a new discrete signal. Decision parameters are the new signal's maximum value and its relative curve position, plus the minimum value and its relative position. These four parameters accurately reflect pulse-shape features.

While many methods (e.g., curve fitting) can calculate leading-edge slope, we used a simplified approach:

$$K_{\text{SLOPE}} = \frac{w[N - M + 1]}{T_{\text{TOTAL\_TIME}}} \quad (17)$$

$$T_{\text{TOTAL\_TIME}} = (N - M) \cdot T \quad (18)$$

where $T_{\text{TOTAL\_TIME}}$ is the effective signal duration and T is the sampling period (8 ns). The new curve's discrete signal $f[n]$ is:

$$f[n] = w[n] - (n - 1) \cdot T \cdot K_{\text{SLOPE}} \quad (19)$$

Maximum C_{MAX} and minimum C_{MIN} values reflecting the leading edge's protrusion are:

$$C_{\text{MAX}} = w[P] - (P - 1) \cdot T \cdot K_{\text{SLOPE}} \quad (20)$$

$$C_{\text{MIN}} = w[Q] - (Q - 1) \cdot T \cdot K_{\text{SLOPE}} \quad (21)$$

where P and Q are the curve's maximum and minimum points. Their relative leading-edge positions are:

$$R_{\text{MAX}} = \frac{P - 1}{N - M} \quad (22)$$

$$R_{\text{MIN}} = \frac{Q - 1}{N - M} \quad (23)$$

The four decision parameters—maximum upper convexity C_{MAX}, minimum lower convexity C_{MIN}, and their relative positions R_{MAX} and R_{MIN}—characterize each pulse signal.

3.3 Analysis of the effect of noise on decision parameters

We analyzed simulated waveforms at 30, 40, and 50 dB signal-to-noise ratios (SNR) to assess noise effects on decision parameters. Waveforms at 16 axial positions (44.5–59.5 mm, 1 mm steps) were generated, and noise was added to achieve the target SNRs. After PSD extraction of decision parameters, we calculated each parameter's mean square deviation (Figure 11 [Figure 11: see original paper]). The decreasing deviation with increasing SNR confirms that noise affects parameter values, necessitating minimal experimental system noise.

3.4 ANN

Artificial neural networks are sophisticated classification tools [44] well-suited for pulse-shape discrimination. We employed a two-layer feedforward network with four input nodes, ten hidden-layer neurons, and two output nodes. The hidden layer used a sigmoid activation function, and the Levenberg–Marquardt backpropagation algorithm served as the training method. Output layer values represent the predicted probability of a full-energy deposition event. The ANN structure is shown in Figure 12 [Figure 12: see original paper].

Based on the four decision parameters, the ANN computes each waveform's event-type probability. Values near 1 indicate high probability of full-energy deposition; values near 0 indicate partial-energy deposition. By setting a threshold, we retain events above the threshold (likely full-energy) and exclude those below (likely partial-energy), maximizing full-energy event retention while suppressing Compton scattering.

4.1 Detector system

Our HPGe signal full-waveform acquisition and analysis system consisted of a lead-shielded compartment, coaxial HPGe detector, high-voltage module, signal-conditioning circuit, full-waveform digital acquisition board, computer, and software. We used a GCDX-40190 N-type coaxial HPGe detector (BSI, Sweden) with 40% relative efficiency and 1.9 keV resolution at 1332 keV. The HPGe crystal measured 63.3 mm in diameter and 59.8 mm in height, with a 7.5 mm cathode diameter. The detector was housed in a 10-cm-thick lead compartment with a copper baffle to block lead X-rays, reducing environmental background interference. Radioactive sources (152Eu, 137Cs, and 60Co) were placed on the detector surface. Cathode and anode biases were -2200 V and 0 V, respectively. The signal-conditioning circuit scaled and biased preamplifier outputs. A 16-bit, 125-Msps digital acquisition board transferred waveform data via PCIe to the computer for storage and analysis. Leading-edge waveform data served as input for subsequent processing. System photographs and framework are shown in Figure 13 [Figure 13: see original paper].

4.2 Data preprocessing

We analyzed 200,000 pulse signals from mixed 152Eu, 137Cs, and 60Co sources, extracting four eigenvalues (C_{MAX}, C_{MIN}, R_{MAX}, R_{MIN}) as decision parameters. Figure 14 [Figure 14: see original paper] shows dot density maps of parameter distributions for each track address. The distinct distributions for full- and partial-energy deposition events enable event-type discrimination.

4.3 ANN training

The ANN assigned different weights to the four decision parameters for event-type determination. We prepared a supervised learning dataset of 207,724 correctly classified waveforms from laboratory measurements, comprising decision parameter sets from 152Eu (344 keV), 137Cs (662 keV), and 60Co (1332 keV) interactions with corresponding flag values. This included 29,154 full-energy deposition events (full-energy peak region, flagged as 1) and 178,570 partial-energy deposition events (Compton plateau region, flagged as 0). Table 3 summarizes the dataset composition. The data were randomly split into training (90%), validation (5%), and testing (5%) subsets. We constructed the network using MATLAB's neural network toolbox with Levenberg–Marquardt backpropagation. The initial learning rate was set within the toolbox and adaptively adjusted during training based on performance. Training ran for 126 epochs on an eight-core workstation. The trained network classified 89,023 newly sampled datasets.

4.4 Validation of pulse-shape simulation

We simulated pulse waveforms from 662 keV γ-ray depositions at multiple radial and axial positions, extracted four decision parameters, and fed them to the trained network for prediction. Figure 15 [Figure 15: see original paper] plots deposition depth versus predicted event-type probability. "Probability" represents the likelihood of full-energy deposition, with higher values indicating greater probability.

In both radial and axial directions, shallow depths (near the surface) yielded low full-energy deposition probabilities. Probability increased with depth, reaching a maximum at intermediate depths before decreasing. This trend matches GEANT4-simulated event distributions (Figure 8), where partial-energy events concentrate at the surface and full-energy events dominate deeper regions. Near the cathode, increasing depth reduces the probability as γ-rays scatter and escape into the cathode more readily, decreasing full-energy deposition likelihood—consistent with Figure 15 curves.

Predicted probabilities were generally lower than experimental values, likely because the experimental environment is more complex, with additional waveform-affecting factors such as dead layers, hole trapping, and electronic noise. However, training the network on experimental waveform decision parameters and redefining thresholds allows the same model to analyze simulated waveform parameters, demonstrating that simulated and experimental waveforms share similar shape characteristics and energy-deposition position trends.

4.5 Energy-spectrum test

After removing ANN-identified Compton scattering event amplitudes, remaining events were processed into energy spectra with suppressed Compton background. Suppression was quantified via Compton suppression factor (F_{CS}) and efficiency (E_{ff}):

$$F_{\mathrm{CS}} = \frac{P/C_{\mathrm{CS}}}{P/C_{\mathrm{original}}} \quad (24)$$

$$E_{\mathrm{ff}} = F_{\mathrm{CS}} \cdot \sqrt{R_{P-P}} \quad (25)$$

where P/C_{original} and P/C_{CS} are peak-to-Compton ratios before and after ANN suppression, and R_{P-P} is the full-energy peak area ratio before and after suppression.

We calculated peak-to-Compton ratios for: 152Eu's 344 keV peak versus 298–339 keV Compton continuum, 137Cs's 662 keV peak versus 680–730 keV continuum, and 60Co's 1332 keV peak versus 1040–1096 keV continuum. Figure 16 [Figure 16: see original paper] shows threshold effects on suppression factor, peak area ratio, and efficiency.

Increasing threshold values raised Compton suppression factors for all sources while decreasing peak area ratios. Compton suppression reduces full-energy peak range counts, which must be balanced against MDA improvement. At a threshold of 0.03, we achieved improved Compton suppression while retaining high full-energy peak counts. Table 4 lists corresponding factors, ratios, and efficiencies. Figure 17 [Figure 17: see original paper] compares logarithmic energy spectra before and after suppression.

4.6 MDA

MDA is calculated as [45-47]:

$$\mathrm{MDA} = \frac{2.71 + 4.65\sqrt{B}}{m \times t \times \varepsilon \times I} \quad (26)$$

where B is background count in the full-energy peak region, m sample mass, t measurement time, ε absolute detection efficiency, and I γ-ray emission intensity.

The MDA ratio (a) compares MDAs before and after Compton suppression for the same measurement, eliminating constants and simplifying calculation. MDA effectively decreases when $a < 1$:

$$a = \frac{2.71 + 4.65\sqrt{B_2}}{2.71 + 4.65\sqrt{B_1}} \cdot \frac{N_1}{N_2} \quad (27)$$

where subscripts 1 and 2 denote pre- and post-suppression values, and N is net peak area count.

Figure 18 [Figure 18: see original paper] shows MDA ratio versus threshold values for the three nuclides. Table 5 gives MDA ratios at 0.03 threshold. The method decreased MDA across a threshold range, with greater reductions at higher γ-ray energies. At 0.03 threshold, MDAs for 344, 662, and 1332 keV peaks decreased by 1.4%, 5.3%, and 21.6%, respectively.

5. Conclusions and Future Work

The proposed method effectively suppressed Compton scattering background across the entire energy range. Compton suppression factors for 152Eu, 137Cs, and 60Co reached 1.13 (344 keV), 1.11 (662 keV), and 1.08 (1332 keV), with corresponding MDA reductions of 1.4%, 5.3%, and 21.6%. Higher incident γ-ray energies yielded greater MDA reductions because full-energy deposition events for high-energy γ-rays concentrate deep in the detector, distinctly different from partial-energy deposition distributions. Thus, ANN removal of partial-energy events retained more full-energy events, reducing full-energy peak count loss and further decreasing MDA.

Beyond coaxial HPGe detectors, this method can be extended to broad-energy HPGe and small-anode HPGe detectors through experimental investigation.

Future work will extract additional leading-edge decision parameters for more accurate shape characterization. Increasing ANN hidden layers and neurons, improving activation functions, and optimizing training algorithms will enhance full- and partial-energy event identification accuracy, thereby improving Compton suppression and reducing MDA.

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