A method based on an artificial neural network for discriminating Compton scattering events in a high-purity germanium γ-ray spectrometer

Authors: Chun-Di Fan, Guo-Qiang Zeng, Hao-Wen Deng, Lei Yan, Jian Yang, Chuan-Hao Hu, Song Qing, Yang Hou, Guo-Qiang Zeng

Date: 2023-12-07T00:00:00+00:00

Abstract

To detect radioactive substances with a low activity level, an anti-coincidence detector and high-purity germanium detector (HPGe) are often used in combination to suppress the Compton scattering background, thereby obtaining an extremely low detection limit and improving the measurement accuracy. However, the complex and expensive hardware system required does not facilitate application and promotion of this method. Thus, a method is proposed to discriminate the digital waveform of pulse signals output by a HPGe detector, whereby the Compton scattering background is suppressed and a low minimum detectable activity (MDA) is obtained without using an expensive and complex anti-coincidence detector and device. The electric field strength distribution and the energy deposition distribution in the detector are simulated to determine the relationship between the pulse shape and location of energy deposition, as well as the characteristics of the energy deposition distribution for full- and partial-energy deposition events. This relationship is used to develop a pulse shape discrimination (PSD) algorithm based on employing an artificial neural network (ANN) for pulse feature identification. To accurately determine the relationship between the deposited energy of gamma (g)-rays in the detector and 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 to the detector. Then, the pulse signals are identified and classified to discriminate between partial- and full-energy deposition events, and some partial-energy deposition events are removed to suppress Compton scattering. The proposed method effectively lowers the MDA of a 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 the corresponding MDAs are lowered by 1.4%, 5.3% and 21.6%.

Full Text

Preamble

A Method Based on an Artificial Neural Network for Discriminating Compton Scattering Events in a High-Purity Germanium γ-Ray Spectrometer

Chun-Di Fan, Guo-Qiang Zeng*, Hao-Wen Deng, Lei Yan, Jian Yang, Chuan-Hao Hu, Song Qing, Yang Hou
College of Nuclear Technology and Automation Engineering, Chengdu University of Technology, Chengdu, China

*Corresponding author. E-mail address: zgq@cdut.edu.cn. Tel.: +1388 193 6804.

Abstract: To detect radioactive substances with low activity levels, anti-coincidence detectors are often combined with high-purity germanium (HPGe) detectors to suppress the Compton scattering background, thereby achieving extremely low detection limits and improved measurement accuracy. However, the required hardware system is complex and expensive, which hinders widespread application and promotion. This paper proposes a method to discriminate the digital waveforms of pulse signals output by an HPGe detector, whereby the Compton scattering background is suppressed and a low minimum detectable activity (MDA) is obtained without using expensive and complex anti-coincidence detectors and electronics. The electric field strength distribution and energy deposition distribution in 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 (PSD) algorithm based on an artificial neural network (ANN) for pulse feature identification. To accurately determine the relationship between the deposited energy of gamma (γ)-rays in the detector and deposition location, we extract four shape parameters from the detector's output pulse signals. Machine learning is then used to input these four shape parameters and identify/classify the pulse signals to discriminate between partial- and full-energy deposition events, removing some partial-energy deposition events to suppress Compton scattering. The proposed method effectively lowers 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 the corresponding MDAs are lowered by 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 (γ)-ray energy in a detector increases the Compton background count in γ-ray spectra and reduces the peak-to-Compton ratio, which adversely impacts both qualitative and quantitative spectral analyses. The anti-coincidence technique is frequently employed for Compton suppression, but this approach requires one or more anti-coincidence detectors with associated electronic circuits, increasing system volume, equipment complexity, and maintenance costs. Pulse shape discrimination (PSD) offers an alternative method for Compton suppression that can lower the Compton scattering background without requiring anti-coincidence detectors or electronics. Instruments using PSD can be designed and manufactured through simple processes, are easy to maintain, and feature low failure rates and costs, making PSD widely applicable to portable and laboratory radiation detection instruments. Consequently, an increasing number of researchers have adopted PSD to suppress Compton scattering backgrounds.

Classical PSD methods—such as those based on A/E features, the trailing edge of the current waveform, and the rising time ratio of the charge waveform—can achieve background suppression by screening single- and multi-point events to enhance the peak-to-Compton ratio of energy spectra. However, background suppression often accompanies loss of full-energy peak counts. In applications requiring MDA reduction, the key challenge lies in deducting background with minimal or no loss of full-energy peak counts, which demands accurate event type screening. Simulation and experimental results demonstrate that pulse shapes output by preamplifiers are affected not only by single- and multi-point events but also depend strongly on the energy deposition location within the detector. Thus, differences in deposition location impact the accuracy of event type identification. In the low-energy region of a detector, the photoelectric effect occurs with high probability, so removing single-point events using traditional PSD increases the likelihood of discarding full-energy deposition events. Consequently, no literature indicates that PSD methods applied to HPGe detection systems have achieved satisfactory background suppression results in the low-energy region. Additionally, pulse waveforms reflect various physical factors such as interaction type and energy deposition location, exhibiting considerable complexity. Multiple physical features of waveforms can describe pulse shape more finely and provide more effective information for event type identification, thereby improving identification accuracy.

In this study, we determine the relationship between pulse shape and energy deposition location and use deposition location to discriminate event types. We introduce a multi-parameter concept to provide more effective information for event type identification and combine it with artificial neural network techniques to screen event types, which effectively improves identification accuracy, enhances the peak-to-Compton ratio, and reduces MDA by deducting substantial background while losing very few full-energy peak counts.

2.1 Modeling the Detector

To investigate the relationship between energy deposition location and pulse shape, we use SolidStateDetectors.jl to model and simulate an HPGe detector. The coaxial HPGe detector has a diameter of 63.6 mm, a height of 59.8 mm, an electrode diameter of 7.5 mm, and an electrode height of 43.5 mm. The three-dimensional structure is shown in Figure 1 [Figure 1: see original paper]. The anode potential is 0 V, the cathode potential is -2200 V, and the bias voltage is 2200 V. The operating temperature is 78 K. A cylindrical impurity concentration distribution model that varies radially and vertically is configured as a simulation parameter, with a central impurity concentration of 5.8$×10^{9}$ atoms · cm^{-3} and an impurity concentration near the cylindrical edge of approximately 6.2$×10^{9}$ atoms · cm^{-3}.

2.1 Field Strength Simulation

The electric field $\vec{E}$ is one of two components required to calculate charge carrier drift trajectories. To calculate the electric field, we solve the Poisson equation for the electric potential $\phi(r)$: $\nabla^2\phi(r) = -\rho(r)$, where $\rho(r)$ represents the spatial charge density, ε_0 denotes the dielectric constant, and ε_r represents the dielectric distribution. The electric field $\vec{E}$ is calculated using $\nabla\vec{E} = \rho(r)$. The open-source software package SolidStateDetectors.jl solves for electric potential and field strength in each grid within the detector using the successive over-relaxation (SOR) algorithm, generating contour plots for equipotential lines and electric field lines. The results are shown in Figure 2 [Figure 2: see original paper].

To calculate the weighting potential distribution of the germanium crystal and determine induced signals on electrodes during charge carrier drift, we solve the weighted potential $\phi(r)$ using the Poisson equation with boundary conditions. Assuming the anode has a weighting potential of 1 V and the cathode has a weighting potential of 0 V, and setting the space charge to zero, the weighting potential distribution inside the detector is obtained through multiple SOR iterations, as shown in Figure 3 [Figure 3: see original paper].

2.3 Drift Velocity Model

The relationship between the drift velocity vector v and electric field vector $\vec{E}$ is given by $v_{e/h} = \mu_{e/h}(\vec{E})\vec{E}(r)$, where $v_{e/h}$ represents the drift velocity of charge carriers (e for electrons, h for holes) and $\mu_{e/h}$ represents charge carrier mobility. Due to the band structure of germanium crystals, conductivity is anisotropic at high electric fields and low temperatures, leading to different drift velocity values in different directions relative to crystal axes. Moreover, if the electric field direction does not align with the crystal's rotational symmetry axis, the drift velocity will have a non-zero angle relative to the applied electric field. The drift velocities $v_{e/h}$ along crystal axes <100>, <110>, and <111> can be described using empirical formulas: $v_{e/h} = (1 + (|\vec{E}|/E_0)^{1/\beta} - \mu_n|\vec{E}|$, where μ_0

represents mobility at low electric fields, $|\vec{E}|$ represents electric field strength, and E_0, β, and μ_n correct the drift velocity.

Under low electric field strength (0.1 kV/cm $\leq$ E $\leq$ 3 kV/cm), the Gunn effect is negligible and mobility becomes isotropic. The fitting parameter μ_0 for mobility is independent of crystal orientation, and the velocity formula simplifies to the previous equation. However, when E $\geq$ 3 kV/cm, the Gunn effect becomes significant and the term μ_{nE} must be added for correction. The AGATA collaboration has determined parameter values for the empirical drift velocity formula under experimental conditions, as shown in Table 1 . These parameters can be configured in the ADLChargeDriftModel configuration file, and SolidStateDetectors.jl utilizes them to accurately simulate charge carrier migration velocity, enabling precise simulations.

2.4 Waveform Simulations

In waveform simulation, charge carrier drift velocity at various detector positions is calculated based on electric field strength distribution and drift velocity models. Initial positions and time steps of charge carriers are set, drift trajectories are computed, and induced charges on electrodes are calculated by combining drift trajectories with weighting potential according to the Shockley-Ramo theorem, which are then converted into voltage pulse waveforms. During simulation, charge carriers are treated as ideal point charges. Based on weighting potential distribution and charge carrier drift velocities, the Shockley-Ramo theorem calculates signal waveforms induced on readout electrodes due to charge carrier drift along their trajectories. For an electron-hole pair created by energy deposition at point r with equal and opposite static charge q, with electron drift trajectory r_e and hole drift trajectory r_h, the induced charge Q(t) at the electrode at time t is: $Q(t) = -q\{\phi[r_h(t)] - \phi[r_e(t)]\}$, where ϕ represents the weighting potential at positions r_e and r_h.

Simulated waveform amplitudes are given in units of charge e_0. For a charge-sensitive preamplifier, induced charges on the detector electrode are integrated on the feedback capacitor and converted into voltage signals while continuous discharge occurs on the feedback resistor. The preamplifier output voltage $U_{out}(t)$ can be approximated by $U_{out}(t) \approx Q(t) \cdot e_0/C_f$, where e_0 is the elementary charge (1.6×10^{-19} C), C_f is the feedback capacitor, and τ is the time constant. In the laboratory detection system, C_f is approximately 0.1 pF and τ is 85 s. Since the pulse rise time is mostly less than 400 ns, computing $e^{-t/\tau}$ yields 0.995   1, allowing us to neglect amplitude loss of the pulse front edge caused by discharge on the preamplifier feedback resistor. The voltage signal can thus be expressed as $U_{out}(t) = Q(t) \cdot e_0$.

Waveforms along multiple axial and radial positions are simulated and analyzed. Along the positive cylindrical axis direction, charge carrier initial height is set from 44.5 mm to 59.5 mm with 1 mm steps, yielding waveforms at 16 positions shown in Figure 4 Figure 4: see original paper. At 25 mm height along the cylindrical axis, charge carrier initial positions are set from 4.5 mm to 30.5 mm radially with 2 mm steps, yielding waveforms at 14 positions shown in Figure 4(b). Three representative waveforms from each direction are selected to compare shape differences, as shown in Figures 4(c) and 4(d). In both directions, energy deposition location significantly impacts pulse waveform shape. Pulses generated near the cathode exhibit fast-to-slow rise times, while those near the anode show slow-to-fast rise times. Pulses at intermediate depth positions exhibit fast-to-slow-to-fast rise times, presenting a reverse-S shape.

2.5 Analysis of Impact of the Charge Cloud Effect

Charge carrier motion is not solely determined by external electric field forces. During carrier drift, diffusion and self-repulsion also play important roles. To simulate these effects, electrons and holes are modeled not as single point charges but as charge clouds composed of multiple point charges. The model incorporates diffusion to describe random thermal motion and self-repulsion to describe repulsive interactions between like carriers, while ignoring attraction between electrons and holes. In SolidStateDetectors.jl, two charge distribution options exist: for charge clouds with fewer than approximately 50 charges, a Platonic polyhedron shell distributes point charges on vertices; for larger clouds (more than 50 charges), point charges are evenly distributed on a regular spherical surface.

The number of charge carriers generated by energy deposition in a high-purity germanium detector is calculated by $n = E/\omega$, where n is the number of carriers, E is deposited energy, and ω is ionization energy. At liquid nitrogen temperature (77 K), the average ionization energy of high-purity germanium is approximately 3 eV. In simulations, deposited energies of 344 keV, 662 keV, and 1332 keV generate approximately 114,667, 220,667, and 444,000 charge carriers, respectively. Therefore, the charge distribution model uses point charges uniformly distributed on a regular spherical surface, with the total charge quantity parameter passed through the NBodyChargeCloud function set to these respective values.

Figure 5 Figure 5: see original paper shows charge pulse waveforms from the electrode under both cloud charge and point charge models for 662 keV energy deposition at position Z=58.5 mm (approximately 1.3 mm from the top anode). When electrons drift toward the anode, those initially close reach it first, while holes drift toward the cathode and arrive later due to greater initial distance. In the point charge model, the large number of electrons is considered as a single point arriving simultaneously, causing rapid signal rise at the anode. In the charge cloud model, electrons are distributed spherically, with boundary electrons reaching the electrode first, followed by central electrons, and finally far-boundary electrons, resulting in gradual electron arrival and relatively slower induced charge amplitude change compared to the point charge model. Subtraction of the two waveforms produces the first pulse shown in Figure 5(b). A similar process for hole drift toward the cathode produces the second pulse. Due to slower hole drift velocity, the charge amplitude change rate during collection is smaller for holes, yielding larger pulse amplitude after subtraction.

Different models thus create certain differences in spatial charge carrier distribution, causing slight variations in induced charge waveforms during carrier drift toward electrodes. Figure 6 Figure 6: see original paper shows the maximum charge difference between the two models for energy depositions at different positions for 344 keV, 662 keV, and 1332 keV. Figure 6(b) shows the maximum relative error. Position changes do not affect the maximum charge difference, but increasing energy deposition increases the maximum difference because larger carrier numbers increase charge cloud radius and distribution density. With increasing radius, complete collection takes longer; with increasing density, charge cloud cardinality increases, creating larger charge quantity differences during the same collection process. The maximum relative error is less than 5% for z = 45.5 mm to 57.5 mm, increasing near electrodes where energy deposition approaches because rapid collection yields smaller waveform data when charge quantity reaches maximum difference, making the relative error calculation larger. However, these values remain below 10%, indicating the charge cloud model's influence on waveform shape is negligible.

2.6 Energy Deposition Location Simulation

We consider two event types: full- and partial-energy deposition. This section determines the relationship between energy deposition location and event type to discriminate between them based on deposition location distribution differences. We use the GEANT4 simulation software package developed by CERN to simulate interaction processes of 344-, 662-, and 1332-keV rays from 152Eu, 137Cs, and 60Co sources entering a coaxial HPGe detector. In GEANT4, QBBC is registered as a physics list including the G4EM standard physics package and G4DecayPhysics package. The detector model uses an N-type coaxial HPGe detector from our laboratory as prototype, with Ge crystal diameter and height of 63.3 mm and 59.8 mm, respectively. A 0.6-mm-thick aluminum piece placed 6.3 mm from the Ge crystal top simulates the detector shell, and a 300-nm-thick borided layer serves as a thin window. Dimensions and positions are shown in Figure 7 Figure 7: see original paper. The radiation source is a planar circular source centered on the detector axis with 63.3 mm diameter, located 40 mm above the detector surface. During simulation, 200,000 gamma rays at each energy are emitted along the negative z-axis, with initial positions and directions shown in Figure 7(b). Gamma rays first pass through aluminum casing and thin window before interacting with the germanium crystal. Transport processes, reaction types, and interaction points at step level inside the crystal are statistically analyzed. Conditional statements select partial-energy deposition events (where previous deposition is within germanium, subsequent ray passes through germanium-medium boundary with kinetic energy > 0) and full-energy deposition events (where previous deposition is within germanium and subsequent ray kinetic energy is 0). Event type selection and coordinate extraction are performed in SteppingAction.cc.

After simulation, incident ray counts, total energy deposition events, full-energy deposition events, and partial-energy deposition events are recorded, as shown in Table 2 . Event coordinates are processed into radius and height, yielding interaction position distributions for both event types in the HPGe detector, as shown in Figure 8 [Figure 8: see original paper]. Results show full-energy deposition events concentrate deep in the detector, while partial-energy deposition events mostly occur at the surface, enabling event type identification by γ-ray energy deposition location. This section has thus analyzed relationships among pulse shape, energy deposition location, and event type, along with the interconnecting mechanisms.

3. Data Processing Algorithm

Combining PSD with machine learning achieves more accurate event identification. We propose a PSD algorithm based on artificial neural network (ANN) pulse feature recognition using four leading-edge waveform features as decision parameters. These four features provide more useful information for event type identification, improving accuracy. The features contribute differently to identification (i.e., have different weights), making manual weight allocation difficult. Therefore, machine learning trains the ANN, enabling continual weight improvement. The model with optimal weights achieves highest event type discrimination accuracy and best Compton scattering event discrimination performance. Training consists of three stages: determining the effective leading-edge range from pulse signals, extracting four decision parameters from this range using PSD algorithm, and building an ANN model with constructed dataset.

3.1 Data Stripping

Gamma rays depositing energy in the detector generate electron-hole pairs that drift under electric fields, manifested in the rising phase of charge-sensitive preamplifier output. We therefore extract the leading-edge waveform for analysis. Each leading-edge waveform contains N_{Total} sampling points. Before PSD algorithm application, we preprocess the leading-edge waveform. Pulse leading-edge amplitude P_{AMP} is calculated as peak amplitude P_{PEAK} minus baseline amplitude P_{BASE}: $P_{AMP} = P_{PEAK} - P_{BASE}$. A prescribed percentage of leading-edge amplitude is extracted to obtain an effective signal range, reducing noise interference and preventing amplitude time walk. Dynamic upper limit TH_{UP} and lower limit TH_{LW} define the effective range: $TH_{UP} = r_{UP} \cdot P_{AMP} + P_{BASE}$ and $TH_{LW} = r_{LW} \cdot P_{AMP} + P_{BASE}$, where r_{UP} and r_{LW} are upper and lower percentages. In this study, r_{UP} and r_{LW} are set to 90% and 10%, with the effective range shown in Figure 9 [Figure 9: see original paper]. Digital signal gain is approximately 12.6 LSB/keV, where LSB denotes the ADC's least significant bit.

For small-amplitude signals, baseline noise may trigger the lower threshold before the signal leading edge. To prevent false triggers, we use reverse signal sampling sequence to capture the lower threshold trigger sequence number and normal sequence for the upper threshold. Trigger sequence numbers must satisfy: $P[M'-1] > TH_{LW}$ and $P[M'] < TH_{LW}$ for the lower threshold, and $P[N] < TH_{UP}$ and $P[N+1] > TH_{UP}$ for the upper threshold, where $P[n]$ is the leading-edge waveform, M' is the reverse sequence number when sampling point is just below lower threshold, and N is forward sequence number when sampling point is just below upper threshold. M' is converted to forward sequence number M by $M = N_{Total} - M'$. After obtaining M and N, waveform $w[n]$ within the effective range is determined by $w[n] = P[M+n-1] - P[M]$, for $n = 1, 2, ..., N-M+1$.

3.2 Feature Extraction

PSD algorithm processing proceeds as follows. First, slope of the effective signal (extracted as described) is calculated. Then, corresponding slope amplitude is subtracted from each discrete signal amplitude within the effective interval to determine a new discrete signal set. Decision parameters are the maximum and minimum values of this new signal and their corresponding relative positions on the curve. These four parameters accurately reflect pulse signal shape features. Many methods such as curve fitting can calculate leading-edge slope, but we simplify processing using: $K_{SLOPE} = w[N-M+1]/T_{TOTAL\_TIME}$, where $T_{TOTAL\_TIME} = (N-M) \cdot T$ is total effective signal time and T is sampling period (8 ns). The new curve's discrete signal $f[n]$ is obtained by subtracting slope discrete values: $f[n] = w[n] - (n-1) \cdot T \cdot K_{SLOPE}$. Maximum C_{MAX} and minimum C_{MIN} values reflecting protruding degree are calculated by $C_{MAX} = w[P] - (P-1) \cdot T \cdot K_{SLOPE}$ and $C_{MIN} = w[Q] - (Q-1) \cdot T \cdot K_{SLOPE}$, where P and Q are maximum and minimum curve positions. Their relative leading-edge positions are $R_{MAX} = (P-1)/(N-M)$ and $R_{MIN} = (Q-1)/(N-M)$. These four decision parameters—C_{MAX}, C_{MIN}, R_{MAX}, and R_{MIN}—characterize pulse signals.

3.3 Analysis of the Impact of Noise on Decision Parameters

We analyzed simulated waveforms to assess impact of different signal-to-noise ratios (30 dB, 40 dB, and 50 dB) on decision parameters. Waveforms at 16 axial positions (44.5–59.5 mm, 1 mm interval) were obtained, with different noise levels added to achieve target SNRs. PSD algorithm extracted decision parameters for each signal, and mean square deviation for each parameter group was calculated and plotted in Figure 11 [Figure 11: see original paper]. The decreasing mean square deviation trend with increasing SNR indicates noise influences decision parameter values, so experimental efforts should minimize system noise.

3.4 ANN

Artificial Neural Networks (ANNs) are modern, powerful classification tools that can distinguish pulse shapes. In this experiment, a two-layer feedforward neural network serves as the ANN model, with an input layer (4 inputs), hidden layer (10 neurons), and output layer (2 neurons). The hidden layer uses sigmoid activation function, and training employs the Levenberg-Marquardt backpropagation algorithm. Output layer data can be interpreted as the probability of predicting a full-energy deposition event. The ANN structure is shown in Figure 12 [Figure 12: see original paper]. Based on four decision parameters extracted from pulse waveforms, the ANN computes predicted probabilities of waveform belonging to particular event types. Results approaching 1 indicate higher probability of full-energy deposition events, while values near 0 suggest partial-energy deposition events. By setting a threshold, events above threshold are retained while those below are excluded, maximizing retention of full-energy deposition events while excluding partial-energy deposition events.

4.1 Detector System

The HPGe signal full-waveform acquisition and analysis system comprises a lead-shielded compartment, coaxial HPGe detector, high-voltage module, signal conditioning circuit, full-waveform digital acquisition board, computer, and upper computer software. A GCDX-40190 N-type coaxial HPGe detector from BSI (Sweden) is used, with 40% relative efficiency and 1.9 keV energy resolution at 1332 keV. The HPGe crystal has diameter and height of 63.3 mm and 59.8 mm, respectively, with a 7.5 mm cathode electrode diameter. The detector is placed in a 10 cm thick lead compartment to reduce environmental background interference, with a copper baffle blocking X-rays from lead decay. Radioactive sources 152Eu, 137Cs, and 60Co are placed on the surface above the detector. Cathode and anode biases are -2200 V and 0 V, respectively. Signal conditioning scales and adjusts preamplifier output pulses. The 16-bit, 125-Msps full-waveform digital acquisition board transmits waveform data via PCIe interface to computer storage. Leading-edge waveform data serves as original data for subsequent study. System figures and framework diagram 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}, and R_{MIN}) as decision parameters. Figure 14 [Figure 14: see original paper] shows dot density maps of decision parameter distributions for each track address. The two event types exhibit different parameter distributions, enabling event discrimination.

4.3 ANN Training

Different weights are assigned to the four decision parameters to determine event type. Extensive iterative ANN training on a dataset is required to determine optimal weight factors. A supervised learning dataset containing correctly classified waveforms from laboratory measurements is prepared, comprising 207,724 decision parameter sets from 152Eu (344 keV), 137Cs (662 keV), and 60Co (1332 keV) interactions with flag values. 29,154 full-energy deposition events within full-energy peak ranges are assigned value 1, and 178,570 partial-energy deposition events within Compton plateau ranges are assigned value 0. Dataset composition is shown in Table 3 . The dataset is randomly divided into training (90%), validation (5%), and testing (5%) subsets. The network is constructed using MATLAB's neural network toolbox with Levenberg-Marquardt backpropagation algorithm, and initial learning rate is encapsulated in the toolbox. During training, learning rate adaptively adjusts based on performance. The model trains for 126 epochs on an eight-core workstation, then classifies events in 89,023 newly sampled datasets.

4.4 Validation of Pulse Shape Simulation

Simulations obtain pulse waveforms from 662 keV gamma ray energy deposition at multiple radial and axial positions. Four decision parameters extracted from simulated waveforms are fed into the neural network model. Energy deposition depth from detector surface and predicted event type probabilities are plotted in Figure 15 [Figure 15: see original paper], where "Probability" represents full-energy deposition event prediction probability. Higher values indicate greater full-energy deposition probability; lower values suggest partial-energy deposition. Regardless of direction, shallow depth (near surface) yields low full-energy deposition probability. As depth increases, probability gradually rises to a maximum, then decreases. This trend aligns with GEANT4 simulation characteristics (Figure 8), where partial-energy events distribute more on outer surfaces and full-energy events in deeper regions. As depth approaches the cathode, gamma ray scattering and escape probability increase, reducing full-energy deposition probability. This matches Figure 15 curves.

Vertical axis probability values are generally lower than those from experimental waveform inference, likely because the experimental environment is more complex than simulation, with additional factors like dead layer effects, hole trapping, and electronic noise creating differences between measured and simulated waveforms. However, training the neural network on experimental waveform decision parameters and redefining thresholds allows the same model to analyze simulated waveform parameters, indicating waveform shape trends remain consistent between environments and with energy deposition position variations.

4.5 Energy Spectrum Test

After removing pulse-signal amplitudes of Compton scattering events identified by the ANN, remaining event amplitudes are processed to produce energy spectra with suppressed Compton backgrounds. Suppression effects are quantified by Compton suppression factor (F_{CS}) and efficiency (E_{ff}), calculated as: $F_{CS} = (P/C_{CS})/(P/C_{original})$ and $E_{ff} = F_{CS} \cdot \sqrt{R_{P-P}}$, 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.

Ratios calculated include: 344 keV full-energy peak height from 152Eu to Compton continuum average height at 298–339 keV; 662 keV peak height from 137Cs to continuum at 680–730 keV; and 1332 keV peak height from 60Co to continuum at 1040–1096 keV. Figure 16 [Figure 16: see original paper] shows threshold value effects on Compton suppression factor, peak area ratio, and efficiency. As threshold increases, Compton suppression factor rises and peak area ratio decreases for all three sources. Compton background suppression reduces full-energy peak range counts, slowing MDA reduction. At threshold 0.03, Compton suppression factor improves while maximizing full-energy peak count retention. Table 4 shows corresponding factors, peak area ratios, and efficiencies. Figure 17 [Figure 17: see original paper] shows logarithmic energy spectra before and after Compton background suppression.

4.6 Minimum Detectable Activity

MDA is calculated using: $MDA = (2.71 + 4.65\sqrt{B})/(m \times t \times \varepsilon \times I)$, where B is background count over full-energy peak range, m is sample mass, t is measurement time, ε is absolute detection efficiency, and I is γ-ray emission intensity. MDA ratio (a) is defined as MDAs before and after Compton suppression for the same measurement, eliminating constants to simplify calculation. MDA effectively decreases when $a < 1$. The computational formula is $a = (2.71 + 4.65\sqrt{B_2})/(2.71 + 4.65\sqrt{B_1})$, where subscripts 1 and 2 denote values before and after suppression, and N denotes net peak area count.

Figure 18 [Figure 18: see original paper] shows MDA ratio versus threshold for the three nuclides. Table 5 shows MDA ratios for 152Eu, 137Cs, and 60Co full-energy peaks at threshold 0.03. According to Figure 18, this method decreases MDA for all three gamma energy levels within a certain threshold range. As gamma ray energy increases, maximum MDA reduction becomes larger. Considering optimization across the entire energy range, threshold 0.03 is selected. At this threshold, MDAs for 344 keV, 662 keV, and 1332 keV full-energy peaks from 152Eu, 137Cs, and 60Co decrease by 1.4%, 5.3%, and 21.6%, respectively.

5. Conclusions and Future Work

The proposed method effectively suppresses Compton scattering background across the entire considered energy range. Compton suppression factors for

152Eu, 137Cs, and 60Co reach 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 ray energy yields larger MDA reduction because full-energy deposition events for high-energy γ-rays concentrate deeper in the detector, differing considerably from partial-energy deposition distributions. Thus, although the ANN removes partial-energy deposition events, more full-energy events are retained than partial-energy events, reducing full-energy peak range count loss and further decreasing MDA.

Beyond coaxial HPGe detectors, further research can extend this method to Broad Energy Germanium (BEGe) and Small Anode Germanium (SAGE) well-type detectors. Future studies will extract more decision parameters from pulse leading edges to characterize edge shape more accurately. Identification and classification accuracy can be improved by increasing ANN hidden layers and neuron counts, enhancing activation functions and training algorithms, thereby improving Compton suppression and decreasing MDA.

Acknowledgments

This research is supported by the National Key R&D Program of China (2022YFF0709503, 2022YFB1902700, 2020YFC1808304-004, 2017YFC0602101) and the Key Research and Development Program of Sichuan Province (2023YFG0347, 2020ZDZX0007).

References

[1] G. F. Knoll, Radiation Detection and Measurement, 3rd edn. (John Wiley & Sons, New York, 2000), pp. 757-

[2] W.H. Zhang, K. Lam, C.L. Liu, A realistic solution of overcoming disadvantage of Compton suppression spectrometer. Appl. Radiat. Isot. 148, 13-18 (2019). doi:10.1016/j.apradiso.2019.03.017

[3] H.M. Badran, T. Sharshar, An experimental method for the optimization of anti-Compton spectrometer. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 435, 423-432 (1999). doi: 10.1016/S0168-9002(99)00573-2

[4] W. Wahl, D. Degering, C. Lierse et al., Enhancement of Compton suppression ratios in anti-Compton techniques: the Garching and Karlsruhe photon spectrometers. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 369, 627-633 (1996). doi: 10.1016/S0168-9002(96)80065-9

[5] M. TSUTSUMI, T. OISHI, N. KINOUCHI et al., Design of an Anti-Compton Spectrometer for Low-Level Radioactive Wastes using Monte Carlo Techniques. J. Nucl. Sci. Tech. 39, 957-963 (2002). doi: 10.1080/18811248.2002.9715282

[6] D.J.G. Love, P.J. Nolan, P.J. Smith et al., The response of a large Ge(Li)/NaI anti-compton system to evaporation neutrons. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 239, 639-640 (1985). doi: 10.1016/0168-9002(85)90047-6

[7] H.M. Badran, T. Sharshar, An experimental method for the optimization of anti-Compton spectrometer. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 435, 423-432 (1999). doi:10.1016/S0168-9002(99)00573-2
[8] Y. Li, W.D. Huang, S.H. Shi et al., The level structure of 76Se from 76Br γ-decay. Nucl. Sci. Tech. 9, 199-208 (1998).
[9] P. Mukherjee, P. Sen, I. Mukherjee et al., On-line neutron response of a Ge NaI(Tl) anti-compton spectrometer. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 251, 191-192 (1986). doi: 10.1016/0168-9002(86)91167-8
[10] H.S. Jung, H.Y. Cho, J.H. Lee et al., Improvement of the Compton suppression ratio of a standard BGO suppressor system by a digital pulse shape analysis. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 580, 1016-1019 (2007). doi:10.1016/j.nima.2007.06.058
[11] M.G. Boulay, M. Kuźniak, Technique for surface background rejection in liquid argon dark matter detectors using layered wavelength-shifting and scintillating thin films. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 968, 163631 (2020). doi: 10.1016/j.nima.2020.163631
[12] K. von Sturm, S. Belogurov, R. Brugnera et al., A Compton scattering setup for pulse shape discrimination studies in germanium detectors. Appl. Radiat. Isot. 125, 163-168 (2017). doi: 10.1016/j.apradiso.2017.04.024
[13] Z. Zeng, Y.-H. Mi, M. Zeng et al., Characterization of a broad-energy germanium detector for its use in CJPL. Nucl. Sci. Tech. 28, 7 (2017). doi:10.1007/s41365-016-0162-y
[14] Y.H. Mi, H. Ma, Z. Zeng et al., Compton suppression in BEGe detectors by digital pulse shape analysis. Appl. Radiat. Isot. 121, 96-100 (2017). doi:10.1016/j.apradiso.2016.12.041
[15] B. Philhour, S.E. Boggs, J.H. Primbsch et al., Simulations of pulse shape discrimination (PSD) techniques for background reduction in germanium detectors. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 403, 136-150 (1998). doi: 10.1016/S0168-9002(97)01071-1
[16] RG. de Orduña, M. Hult, E. Andreotti et al., Pulse shape analysis to reduce the background of BEGe detectors. J. Radioanal. Nucl. Chem. 286, 477-482 (2010). doi: 10.1007/s10967-010-0729-8
[17] Y.-H. Mi, Z. Zeng, H. Ma et al., Improving detection sensitivity of a low background BEGe spectrometer by pulse shape discrimination using rise-time ratio. J. Radioanal. Nucl. Chem. 325, 183-189 (2020). doi:10.1007/s10967-020-07191-9
[18] Duan, Budjá, Marik et al., Pulse shape discrimination studies with a Broad-Energy Germanium detector for signal identification and background suppression in the GERDA double beta decay experiment. J. Instrum. 4, P10007 (2009). doi:10.1088/1748-0221/4/10/p10007
[19] D. Beckedahl, J. J. Blair, A. Friensehner et al., Compton rejection for HPGe detectors via real-time pulse shape analysis. Paper Presented at the 39th Annual Institute of Nuclear Materials Management Meeting, Naples, Florida,

26-30 July 1998
[20] G.J. Schmid, D. Beckedahl, J.J. Blair et al., HPGe compton suppression using pulse shape analysis. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 422, 368-372 (1998). doi: 10.1016/S0168-9002(98)00985-1
[21] J.H. Lee, H.S. Jung, H.Y. Cho et al., A Novel Digital Pulse-Shape Analysis for High-Resolution Position-Sensitive Gamma-Ray Spectroscopy. IEEE Transactions on Nuclear Science. 57, 2631-2637 (2010). doi:10.1109/TNS.2010.2053385
[22] J.Y. Moon, C.S. Lee, Position determination of interaction points inside a planar-type segmented germanium detector by pulse shape analysis using a three-dimensional Green's function. Nucl. Phys. A. 746, 643-646 (2004). doi:10.1016/j.nuclphysa.2004.09.042
[23] H.Y. Cho, C.S. Lee, J.Y. Moon et al., Pulse shape analysis of induced charges in a segmented germanium detector by using the weighting potential method. J. Korean Phys. Soc. 45, 1485-1489 (2004).
[24] M. Kurokawa, S. Shimoura, H. Iwasaki et al., Pulse shape simulation and analysis of segmented Ge detectors for position extraction. IEEE Trans. Nucl. Sci. 50, 1309-1316 (2003). doi:10.1109/TNS.2003.818238
[25] I. Abt, A. Caldwell, D. Lenz et al., Pulse shape simulation for segmented true-coaxial HPGe detectors. Eur. Phys. J. C. 68, 609-618 (2010). doi:10.1140/epjc/s10052-010-1364-9
[26] R.-M.-J. Li, S.-K. Liu, S.-T. Lin et al., Identification of anomalous fast bulk events in a p-type point-contact germanium detector. Nucl. Sci. Tech. 33, 57 (2022). doi:10.1007/s41365-022-01041-x
[27] L.J. Harkness-Brennan, D.S. Judson, A.J. Boston et al., An experimental characterisation of a Broad Energy Germanium detector. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 760, 28-39 (2014). doi:10.1016/j.nima.2014.05.080
[28] D. Barrientos, A.J. Boston, H.C. Boston et al., Characterisation of a Broad Energy Germanium (BEGe) detector. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 648, S228-S231 (2011). doi: 10.1016/j.nima.2010.11.129
[29] C. Unsworth, A.J. Boston, H.C. Boston et al., Characterisation of a small electrode HPGe detector. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 927, 293-300 (2019). doi:10.1016/j.nima.2019.02.043
[30] M. Nakhostin, Z. Podolyak and P.J. Sellin, Application of pulse-shape discrimination to coplanar CdZnTe detectors. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 729, 541-545 (2013). doi:10.1016/j.nima.2013.07.073
[31] C.-F. Yang, C.-Q. Feng, S.-B. Liu et al., FPGA-based α/γ pulse shape discrimination for BaF2 detector using 2 Gsps fast waveform sampling. Nucl. Sci. Tech. 28, 19 (2017). doi: 10.1007/s41365-016-0173-8
[32] J.-L. Cai, D.-W. Li, P.-L. Wang et al., Fast pulse sampling module for real-time neutron-gamma discrimination. Nucl. Sci. Tech. 30, 84 (2019). doi:

10.1007/s41365-019-0595-1
[33] J.Q. FAISAL, J.-L. Lou, Z.-H. Li et al., A pulse shape discrimination of CsI(Tl) crystal with 6He beam. Nucl. Sci. Tech. 21, 35-38 (2010). doi: 10.13538/j.1001-8042/nst.21.35-38
[34] K.-N. Li, X.-P. Zhang, Q. Gui et al., Characterization of the new scintillator Cs2LiYCl6:Ce3+. Nucl. Sci. Tech. 29, 11 (2018). doi: 10.1007/s41365-017-0342-4
[35] I. Abt, F. Fischer, F. Hagemann et al., Simulation of semiconductor detectors in 3D with SolidStateDetectors.jl. J. Instrum. 16, P08007 (2021). doi: 10.1088/1748-0221/16/08/P08007
[36] L Mihailescu, W Gast, R.M Lieder. The influence of anisotropic electron drift velocity on the signal shapes of closed-end HPGe detectors. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 447, 350-360 (2000). doi: 10.1016/S0168-9002(99)01286-3
[37] Bart Bruyneel, Peter Reiter, Gheorghe Pascovici. Characterization of large volume HPGe detectors. Part I: Electron and hole mobility parameterization. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 569, 764-773 (2006). doi: 10.1016/j.nima.2006.08.130
[38] Bart Bruyneel, Peter Reiter, Gheorghe Pascovici. Characterization of large volume HPGe detectors. Part II: Experimental results. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 569, 774-789 (2006). doi: 10.1016/j.nima.2006.08.129
[39] M. Nakhostin, Signal Processing for Radiation Detectors. (John Wiley & Sons, New York, 2018), pp. 6-7
[40] J. Allison, K. Amako, J. Apostolakis et al., Recent Developments in Geant4. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 835, 186-225 (2016). doi: 10.1016/j.nima.2016.06.125
[41] J. Allison, K. Amako, J. Apostolakis et al., Geant4 Developments and Applications. IEEE Trans. Nucl. Sci. 53, 270-278 (2006). doi: 10.1109/TNS.2006.869826
[42] S. Agostinelli ae, J. Allison, K. Amako et al., Geant4 - A Simulation Toolkit. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 506, 250-303 (2003). doi: 10.1016/S0168-9002(03)01368-8
[43] H.-T. Jia, S.-T. Lin, S.-K. Liu et al. High-accuracy measurement of Compton scattering in germanium for dark matter searches. Nucl. Sci. Tech. 33, 157 (2022). doi: 10.1007/s41365-022-01148-1
[44] J. Yang, Y.L. Li, Y. Tian et al., Identification of single-pixel incomplete charge collection events by using cathode waveform in pixelated CdZnTe detectors. J. Instrum. 15, P09017-P09017 (2020). doi:10.1088/1748-0221/15/09/P09017
[45] X.-C. Ming, H.-F. Zhang, R.-R. Xu et al. Nuclear mass based on the multi-task learning neural network method. Nucl. Sci. Tech. 33, 48 (2022). doi: 10.1007/s41365-022-01031-z
[46] G.R. Gilmore, Practical Gamma-Ray Spectrometry, 2nd edn. (John Wiley & Sons, New York, 2008), pp. 117-
[47] G. Baccolo, A. Barresi, M. Beretta et al., Development of a low background

alpha–beta/gamma coincidence detector. Nucl. Instrum. Methods Phys. Res. Sect. A-Accel. Spectrom. Dect. Assoc. Equip. 1003, 165290 (2021). doi: 10.1016/j.nima.2021.165290
[48] Y. Gu, K. Sun, L.-Q. Ge et al. Investigating the minimum detectable activity concentration and contributing factors in airborne gamma-ray spectrometry. Nucl. Sci. Tech. 32, 110 (2021). doi: 10.1007/s41365-021-00951-6

Note: Figure translations are in progress. See original paper for figures.