Generalization Ability of a CNN γ-ray Localization Model for Radiation Imaging

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Abstract

In γ-ray imaging, localization of the γ-ray interaction in the scintillator is critical. Convolutional neural network (CNN) techniques are highly promising for improving γ-ray localization. Our study evaluated the generalization capabilities of a CNN localization model with respect to the γ-ray energy and thickness of the crystal. The model maintained a high positional linearity (PL) and spatial resolution (SR) for ray energies between 59–1460 keV. The PL at the incident surface of the detector was 0.99, and the resolution of the central incident point source ranged between 0.52–1.19 mm. In modified uniform redundant array (MURA) imaging systems using a thick crystal, the CNN γ-ray localization model significantly improved the useful field-of-view (UFOV) from 60.32% to 93.44% compared to the classical centroid localization methods. Additionally, the signal-to-noise ratio (SNR) of the reconstructed images increased from 0.95 to 5.63.

Full Text

Abstract

In γ-ray imaging, precise localization of γ-ray interactions within the scintillator is critical for image quality. Convolutional neural network (CNN) techniques show exceptional promise for enhancing γ-ray localization accuracy. This study systematically evaluated the generalization capabilities of a CNN-based localization model with respect to both γ-ray energy and crystal thickness. The model maintained high positional linearity (PL) and spatial resolution (SR) across a broad energy range of 59–1460 keV, achieving a PL of 0.99 at the detector's incident surface and an SR ranging from 0.52 to 1.19 mm for a central incident point source. In Modified Uniform Redundant Array (MURA) imaging systems employing thick crystals, the CNN localization model dramatically improved the useful field-of-view (UFOV) from 60.32% to 93.44% compared to classical centroid localization methods. Additionally, the signal-to-noise ratio (SNR) of reconstructed images increased from 0.95 to 5.63, demonstrating substantial performance gains.

Keywords: γ-ray imaging; γ-ray localization model; convolutional neural network; spatial resolution

1. Introduction

Gamma-ray imaging enables the spatial mapping of radioactive isotope distributions, offering unique advantages for radioactivity monitoring with applications spanning homeland security, public safety, nuclear industry, and medical imaging. In scintillator-based γ-ray imaging systems, the distribution of scintillation light generated by γ-ray interactions represents a crucial intermediate step for estimating incident γ-ray interaction positions. Localization algorithms have been developed to expand the useful field-of-view (UFOV) of crystals, enhance detector spatial resolution (SR), and mitigate image distortion arising from hardware nonuniformity \cite{1–4}. Traditional γ-imaging localization algorithms include lookup tables, maximum likelihood estimation, classical center-of-gravity (COG), threshold-center-of-gravity (TCOG), and raise-to-power (RTP) methods \cite{5–7}. While lookup table and maximum likelihood methods significantly improve imaging performance, they require extensive experimental characterization to obtain optical photon response functions during initial setup.

The COG and TCOG methods have gained widespread adoption due to their computational efficiency and simple electronic implementation. The COG method estimates interaction locations by calculating the center of gravity of the scintillation light distribution. However, this approach suffers from light-field shrinkage effects, resulting in degraded resolution at image edges and reduced detector UFOV [?]. Artificial intelligence techniques have recently been applied to γ-ray imaging systems. K-nearest neighbor (KNN) networks have been used for photon interaction positioning in PET and Compton cameras, achieving resolutions up to 3 mm \cite{9–10}, though long computation times and extensive calibration requirements limit their practical application [?]. Feed-forward neural networks (FFNNs), including multilayer perceptron (MLP) and radial basis function (RBF) architectures, have also been employed for γ-ray localization \cite{12–18}. Compared to KNN, FFNNs offer higher spatial resolution and faster computation.

Convolutional neural networks (CNNs) provide additional advantages over FFNNs, including superior computational speed and more efficient storage scaling. CNN applications in radiation imaging have demonstrated excellent spatial resolution, revealing substantial potential for further development in nuclear applications \cite{19–25}. In previous work, we developed a gamma imaging system based on monolithic LaBr3(Ce) crystals [?]. By accurately modeling optical photon transport within the LaBr3(Ce) crystal, we obtained scintillation photon distribution responses and developed a CNN-based γ-ray localization model. This study investigates the generalization capability of our CNN localization model across varying crystal thicknesses and γ-ray energies, establishing an imaging detector model based on physical detector parameters, a CNN localization model, and a Modified Uniform Redundant Array (MURA) imaging system. The CNN localization model significantly mitigates shrinkage effects and improves image signal-to-noise ratio (SNR) in thick-crystal imaging systems, demonstrating robust generalization across a wide γ-ray energy spectrum.

2. Materials and Methods

We utilized Geometry And Tracking 4 (Geant4) and PyTorch to construct a Monte Carlo detector model, MURA imaging system, and CNN γ-ray localization model. First, Geant4 established an LaBr3(Ce) detector model based on physical detector specifications, incorporating accurate electromagnetic and optical processes. Second, we obtained a detector response matrix for neural network training and trained the CNN model for γ-ray localization using PyTorch. Third, the trained CNN network localized γ-ray interactions, and we analyzed the localization results.

2.1 Model of Imaging Detector

This study employed Geant4 and PyTorch for imaging experiments and neural network training. The Geant4 simulation code comprised two systems: flood-field irradiation and MURA imaging. The flood-field irradiation system, consisting of an imaging detector model and uniform irradiation source, generated the dataset for neural network training and generalization testing. The MURA imaging system, comprising an imaging detector model, MURA collimator, and circular source, evaluated imaging performance across different localization algorithms. Using PyTorch, we built a CNN γ-ray localization model to train weight parameters and predict ray interaction points.

[Figure 1: see original paper] Flood-field irradiation system, MURA imaging system, and CNN structure.

Flood-field irradiation system: The detector model consisted of a monolithic LaBr3(Ce) crystal (51 mm × 51 mm × 5 mm) coupled to a silicon photomultiplier (SiPM) array. The 16 × 16 SiPM array (Micro-30035-TSV, ONSEMI) featured sensitive and package areas of $3.07 \times 3.07\ \text{mm}^2$ and $3.16 \times 3.16\ \text{mm}^2$, respectively, as shown in Fig. 1(A). Teflon (0.3 mm thick) served as a diffuse reflective layer, encapsulated in aluminum foil (0.5 mm) as a reflective mirror layer, with 3 mm thick glass at the crystal bottom. Optical grease (0.1 mm thick, refractive index 1.41) functioned as a light guide between the glass and SiPM array.

Accurate optical processes must be included in the model alongside physical electromagnetic processes because detector responses are obtained through the

SiPM array. In Geant4, optical photons are distinct from high-energy γ photons and are not subject to energy conservation; their energies must not be tallied as part of physical event balances. Electromagnetic processes in the detector include the photoelectric effect, Compton scattering, electron-positron pair production, ionization, bremsstrahlung, and multiple scattering. Optical processes encompass scintillation, Cherenkov radiation, Rayleigh scattering, Mie scattering, bulk absorption, refraction, and reflection (specular spike (SS), specular lobe (SL), Lambertian (L), and backscatter (BS)).

Optical photon transport involves two categories: transport within materials, requiring specification of material parameters, and transport between different media, requiring surface parameter definitions. Material parameters control optical photon generation and transport within materials, while surface parameters govern physical processes at media interfaces. Material parameters primarily include intrinsic scintillator properties: emission spectrum, scintillation yield, intrinsic resolution, and time constant. Surface parameters mainly comprise surface type, surface finish, detection efficiency, reflectivity, and reflection type.

Optical photon transport across boundaries depends on the boundary type between dielectric materials. Primary boundary types include dielectric-dielectric and dielectric-metal interfaces. At dielectric-dielectric boundaries between two dielectric materials, optical photons undergo refraction and reflection based on wavelength, incident angle, and refractive indices. At dielectric-metal boundaries between transparent media and metals, optical photons may be absorbed by the metal surface or reflected back into the transparent medium, with absorption recorded based on the photon detection efficiency (PDE). In this study, Teflon, SiPM, and LaBr3(Ce) surfaces featured dielectric-metal, dielectric-metal, and dielectric-dielectric boundaries, respectively.

During flood-field irradiation simulation, 122, 365, 662, and 1332 keV γ rays vertically irradiated the detector's incident surface. Upon γ-ray interaction, the detector emitted isotropic scintillation photons at the interaction point according to the energy deposited. For scintillation photons reaching encapsulation surfaces (aluminum foil or Teflon), the simulation modeled total reflection, refraction, or reflection based on photon wavelength, incident angle, and material refractive indices. Scintillation photons reaching the SiPM surface converted to electron-hole pairs based on photon wavelength and SiPM PDE, with the number of pairs recorded [**?**]. Scintillation photons from each event were recorded by the SiPM array to form a response matrix, as shown in Fig. 1(A). The detector model output the corresponding matrix and two-dimensional coordinates of incident γ rays for each event. The matrix was normalized for neural network training, with coordinates serving as labels.

MURA imaging system: Fig. 1(B) illustrates the MURA imaging system. The MURA-coded aperture collimator consisted of tungsten with dimensions 72.7 × 72.7 × 5 mm. The circular source emitted γ rays at energies of 59 keV (^{241}Am), 122 keV (^{57}Co), 140 keV (^{99}mTc), 365 keV (^{131}I), 662 keV (^{137}Cs), 779 keV (^{152}Eu), 1332 keV (^{60}Co), and 1460 keV (^{40}K). The source-to-collimator distance was 180 mm, and the collimator-to-detector surface distance was 50 mm, with source, coding plate, and detection planes parallel and coaxial.

During γ imaging simulation, radiation from the source passed through the collimator, deposited energy in the detector, and generated scintillation photons. These photons, after reflection and refraction within the detector, were absorbed by the SiPM array, producing a scintillation distribution response. We then used multiple algorithms (CNN, Anger, RTP, TCOG (=0.2%), TCOG (=0.5%)) with the detector response matrix to calculate interaction coordinates and accumulate events for encoded image formation. The MELM algorithm subsequently decoded the coded image to reconstruct the radiation source shape [**?**].

CNN structure: The CNN was implemented in PyTorch, comprising nine convolutional layers and three fully connected layers, with two average pooling layers connecting convolutional layers of different dimensions, as shown in Fig. 1(C). In the CNN, each event's response matrix from the SiPM array was represented as a 16 × 16 tensor input. Following feature extraction by convolutional layers and regression by fully connected layers, the network output 2-D coordinates. Hardware parameters for CNN development are listed in Table 1 .

2.2 CNN Model Training and Testing

To enhance generalization capability, we used 1×10^6 samples (event response matrices) for CNN training, 2×10^4 samples for validation and overfitting prevention, and 3.6×10^5 samples for localization testing. Training employed 122, 365, 662, and 1332 keV γ rays vertically irradiating a 5 mm thick crystal to obtain response matrices. We used mean square error (MSE) as the loss function, with weights iteratively updated via the Adam algorithm. The learning rate was set to 1×10^{-4}, and batch size was 16. The MSE function was defined as:

$$MSE = \sum (y_i - \hat{y}_i)^2 \times D, \quad (1)$$

where i is the sample number, m is the total number of samples, y_i and $\hat{y}_i$ are the label and predicted values for sample i, respectively, and D is the length of the detector's incident surface.

MSE values for different datasets are listed in Table 2 , ranging between 0.51–0.58. The close agreement between test and training set MSEs indicates strong generalization capability.

2.3 Classical Localization Algorithm

The COG algorithm, proposed by Anger, represents a classical γ-imaging localization method that uses photoelectric device center coordinates as linear weights to calculate photon interaction positions:

$$X_{Anger} = \frac{\sum_{k=1}^{n} x_k c_k}{\sum_{k=1}^{n} c_k}, \quad (2)$$

where X_{Anger} is the incident photon coordinate in the x-direction, x_k represents the center position coordinate of the kth SiPM in the x-direction, c_k is the signal collected by the kth SiPM, and n is the number of SiPMs in the x-direction. The same equation applies to the y-direction.

COG localization results exhibit strong shrinkage effects in γ-imaging devices due to nonuniformity in scintillators and photoelectronic devices [?], compressing localization results toward the image center and reducing UFOV while enhancing nonuniformity. Wojcik et al. proposed the truncated center of gravity (TCOG) method to reduce shrinkage by applying a threshold [?], using only signals above the threshold for position calculation while setting sub-threshold signals to zero:

$$X_{TCOG} = \frac{\sum_{k=1}^{n} x_k \times (c_k - \theta \times c_k)}{\sum_{k=1}^{n} (c_k - \theta \times c_k)}, \quad (3)$$

where θ is the threshold. In this study, $\theta_1 = 0.002$ and $\theta_2 = 0.005$. The same formula applies in the y-direction. To improve TCOG performance, the raise-to-power (RTP) algorithm was proposed:

$$X_{RTP} = \frac{\sum_{k=1}^{n} x_k \times (c_k - \theta \times c_k)^{\alpha}}{\sum_{k=1}^{n} (c_k - \theta \times c_k)^{\alpha}}, \quad (4)$$

where α is a power exponent; in this study $\alpha = 2$ and $\theta = 0.005$. The RTP algorithm applies nonlinear power operations to signals, increasing position weights for large signals while decreasing weights for small signals, thereby positioning results near strong signal locations [?]. Compared to TCOG, RTP more effectively eliminates small signal influence and reduces shrinkage effects.

3. Results and Discussion

We evaluated the energy generalization ability (EGA) and thickness generalization ability (TGA) of the CNN γ-ray localization model by systematically varying ray energy and crystal thickness. For EGA assessment, we tested PL and SR using γ rays at 59, 122, 140, 365, 662, 779, 1332, and 1460 keV. We also compared multiple localization algorithms—including CNN, Anger, RTP, TCOG ($\theta_1 = 0.002$), and TCOG ($\theta_2 = 0.005$)—to evaluate the CNN model's TGA.

3.1 EGA of the CNN γ-Ray Localization Model

Positional linearity (PL) quantifies the deviation between measured event positions and mechanical reference points using the L-factor [?]:

$$L\text{-factor} = \frac{\Delta X_{measurement}}{\Delta X_{mechanical}}, \quad (5)$$

where $\Delta X_{measurement}$ is the displacement of measured points, $\Delta X_{mechanical}$ is the displacement of mechanical points, and the L-factor represents the slope of the linear curve at each measurement point. In linear response, measured and mechanical coordinates follow $y = slope \times x + intercept$, with PL represented by the slope value. In this study, the detector's lower left corner served as the origin, establishing a coordinate system with 1 mm minimum scale and 0–51 mm axis range. We step-scanned the detector along the scan path using various γ-ray energies. In Fig. 3 Figure 3: see original paper, red dotted lines indicate the scanning path, black dots represent mechanical points, and adjacent mechanical points are separated by 2.5 mm.

The CNN model calculated interaction positions for γ rays of different energies at each scanning point, generating a PL map for all mechanical points (2.5 mm step-scanning) shown in Fig. 2 Figure 2: see original paper. The dashed line in Fig. 2(B) represents ideal PL where measured and mechanical points coincide with slope = 1. As shown, PL values for all energy rays between 2.5–50 mm range closely follow the dashed line, with slopes ranging from 0.98–0.99. The CNN model demonstrates excellent PL for rays spanning 59–1460 keV, confirming sufficient EGA for interaction position prediction across this energy range.

Fig. 3 presents step-scan images for various γ-ray energies. As shown in Fig. 3(B–F), mechanical point SR varied between 0.52–0.76 mm for γ-ray energies of 122–779 keV. For 59 keV and 1332–1460 keV energies (Fig. 3(A, G, H)), SR ranged from 1.05–1.19 mm. The SR at mechanical points was considered the crystal SR ($SR_{crystal}$) [?]. The CNN model accurately localized γ-ray interaction positions across the entire 59–1460 keV energy range, exhibiting strong energy response and robust EGA.

Fig. 4 [Figure 4: see original paper] presents MURA system reconstructed images of circular sources (10 mm diameter) emitting various γ-ray energies. Reconstructed image SNRs were high, ranging from 5.8–15.5 for ray energies of 59–779 keV. At 1332 and 1460 keV, SNRs decreased to 1.0 and 0.84, respectively.

At low incident ray energies, the photoelectric effect cross-section exceeds that of the Compton effect, allowing the collimator to effectively absorb rays with minimal scattering and high imaging SNR. As energy increases, the Compton effect cross-section rises, causing γ-ray interactions with the MURA-coded aperture collimator to produce scattered rays that the detector absorbs. These scattered ray interactions interfere with the encoded image, reducing SNR. In the

1332–1460 keV range, increasing Compton and electron-positron pair production cross-sections further decrease SNR because scattered photons from multiple scattering events and electrons from pair production alter the detector's scintillation light distribution, affecting CNN positioning accuracy and encoded image precision. At high γ-ray energies, the MURA-coded aperture collimator cannot effectively absorb rays, allowing numerous high-energy rays to penetrate the collimator and be partially or fully absorbed by the detector, significantly disturbing the encoding process and reducing encoded image accuracy.

As shown in Fig. 4(I–L), we obtained reconstructed images by tracking ray transport in the model while ignoring Compton scattering events from the collimator. Compared to Fig. 4(E–H) that include scattering, the SNR for 1332 keV rays improved from 1.0 to 5.7, and for 1460 keV rays from 0.84 to 5.0. This demonstrates that scattered high-energy rays significantly impact reconstructed image SNR, highlighting the need to consider scattered ray effects in γ-ray imaging systems. Collimator thickness and material substantially affect ray absorption and imaging quality.

Beyond incident ray energy E_γ, MURA system imaging resolution $SR_{detector}$ depends on both detector resolution $SR_{crystal}$ and collimator resolution $SR_{collimator}$:

$$(SR_{detector})^2 = (SR_{collimator})^2 + (SR_{crystal})^2. \quad (6)$$

We calculated the relative error R between reconstructed source diameter ($D_{reconstructed}$) and simulated source diameter ($D_{simulated}$) using:

$$R = \frac{|D_{reconstructed} - D_{simulated}|}{D_{simulated}} \times 100\%. \quad (7)$$

Table 3 lists these relative errors. Compared to 365 keV γ-rays, the crystal SR exceeds 1 mm at 59 keV, resulting in poorer system SR and larger relative geometric error for the reconstructed radioactive source. For γ-ray energies of 122–365 keV, the collimator effectively absorbs incident rays while maintaining high crystal SR, yielding the smallest relative error for circular source diameter in reconstructed images. At 662–1460 keV, high-energy γ-rays and scattered rays are directly absorbed by the detector, strongly affecting the projected image and increasing relative reconstruction error with rising energy.

Although only four γ-ray energies were used to train the CNN localization model, the model accurately localized unknown-energy rays across 59–1460 keV with good PL and SR, demonstrating excellent localization and EGA characteristics. A MURA imaging system based on this neural network model successfully reconstructed radiation source shapes across 59–1460 keV, indicating broad applicability of this localization approach.

3.2 Thickness Generalization Ability of the CNN γ-Ray Localization Model

We applied the CNN localization model to crystals of 5 mm and 10 mm thickness, calculating PL and SR of mechanical points to evaluate thickness generalization. In addition to the CNN model, we compared TCOG-0.002, TCOG-0.005, RTP, and Anger algorithms.

Fig. 5 [Figure 5: see original paper] shows PL and SR for mechanical points in 5 mm and 10 mm thick crystals. PL calculations appear in Fig. 5(A–B). For 5 mm crystals, CNN, RTP, and TCOG-0.005 achieved higher PL than TCOG-0.002 and Anger. When crystal thickness increased to 10 mm, RTP, TCOG-0.005, and TCOG-0.002 algorithm slopes decreased from 0.97 to 0.92, 0.94 to 0.92, and 0.42 to 0.38, respectively. The Anger algorithm slope decreased from 0.37 to 0.33, while the CNN slope remained nearly unchanged. Comparison of Figs. 5(A) and (B) reveals that the CNN model achieves the best PL for a given thickness, and under the same algorithm, thick crystals exhibit worse PL than thin crystals. This occurs because shrinkage effects intensify with increasing crystal thickness, altering light distribution range and degrading traditional algorithm localization performance. In contrast, the CNN localization model reduces shrinkage and maintains high PL in thick-crystal detectors.

SR values for scanned points at different thicknesses appear in Fig. 5(C–D). For the same crystal thickness, the four Anger-based algorithms showed similar SR in the central region. At edges, the CNN model achieved higher spatial resolution than Anger due to superior shrinkage reduction. Using identical crystal thickness, the CNN model obtained better SR at both center and edges, with significantly higher accuracy than other algorithms.

Comparing Figs. 5(C) and (D), increased crystal thickness from 5 to 10 mm intensified boundary reflection layer shrinkage effects, degrading SR. Specifically, SR values decreased from 2.92 to 3.72 mm (Anger), 0.99 to 1.29 mm (TCOG-0.002), 0.98 to 1.33 mm (TCOG-0.005), 0.95 to 1.31 mm (RTP), and 0.62 to 0.72 mm (CNN). The CNN SR decrease was smallest, indicating minimal shrinkage effect impact.

Although trained on 5 mm thick crystal data, the CNN successfully predicted ray interaction positions in 10 mm thick crystals, demonstrating strong thickness generalization ability (TGA).

Fig. 6 [Figure 6: see original paper] shows UFOV values for 5 mm and 10 mm thick crystals under different algorithms. High PL significantly contributes to large UFOV and high SR. The proposed CNN model's high PL accurately determines incident ray positions, including at edges, without central compression, substantially reducing shrinkage effects and improving both spatial resolution and UFOV.

UFOV calculations for detectors with 5 mm and 10 mm crystals appear in Fig. 6. The CNN model achieved the largest UFOV, while Anger produced the smallest at each thickness. As shown in Fig. 6(A3–A5), the CNN model's UFOV increased by 26.48% and 17.83% compared to TCOG-0.002 and TCOG-0.005, respectively, demonstrating effective UFOV improvement.

Compared to other algorithms, CNN model images showed less edge shrinkage effect, with vertex and center counts closely matched, indicating significantly improved uniformity. For 10 mm crystals, UFOV values from RTP and TCOG-0.005 decreased by 10.24% and 9.77%, respectively, compared to 5 mm crystals, while the CNN model's UFOV decreased by only 3.60%. This confirms that the CNN localization model most effectively reduces shrinkage effect influence.

Fig. 7 [Figure 7: see original paper] presents MURA imaging results for 5 mm and 10 mm crystals using different algorithms, showing reconstructed images of a 6 mm diameter circular source. For the 5 mm crystal detector (Fig. 7(A1–A2)), Anger and TCOG-0.002 algorithms suffered severe shrinkage effects, yielding small UFOV areas that prevented full collimator projection onto the detector and thus failed to reconstruct radioactive sources. As shown in Fig. 6(A3–A5), TCOG-0.005, RTP, and CNN achieved UFOVs of 70.56%, 79.21%, and 97.04%, respectively, providing sufficient UFOV for complete MURA collimator projection in encoded images and enabling circular source imaging (Figs. 7(a), (3), and (5)). Regarding image quality, the CNN model demonstrated superior PL with less distortion and aberration in MURA-projected images compared to TCOG-0.005 and RTP, yielding the highest SNR in reconstructed images. The CNN-based reconstructed image showed the smallest diameter error among the three algorithms, attributable to the CNN model's highest SR and smallest projection error, which indirectly reduced circular source reconstruction error.

For the 10 mm thick crystal (Fig. 7(B1–B5)), increased shrinkage effects reduced localization algorithm accuracy and increased MURA projection distortion. Except for the CNN model, imaging systems based on other algorithms could not reconstruct ray sources. Only the CNN localization model effectively reduced shrinkage effects on reconstructed images, producing high-SNR images with small circular source diameter errors. These imaging results demonstrate that thick crystals can be effectively employed in MURA imaging systems when using the CNN localization model.

3.3 Advantages of the CNN Localization Model

Compared to classical algorithms, the CNN γ-ray localization model offers two principal advantages. First, by effectively improving detector PL and SR, the CNN significantly enhances UFOV. In MURA imaging systems, larger UFOV increases projected image integrity, raises reconstructed image SNR, and reduces reconstruction errors. Second, the CNN model effectively mitigates shrinkage effects, providing strong EGA and TGA. The EGA enables wide-energy imaging capabilities, while TGA allows imaging with thick crystals.

Classical γ cameras employ thin crystals to avoid shrinkage-induced distortion and aberration, but this approach yields lower detection efficiency, poorer energy resolution, and longer imaging times. The CNN localization model overcomes these limitations by enabling effective use of thicker crystals.

4. Conclusion

This study evaluated the CNN γ-ray localization model's generalization ability across incident γ-ray energies and detector crystal thicknesses. The CNN model predicted interaction positions for γ-rays ranging from 59–1460 keV in detector crystals, achieving high PL values (0.98–0.99) and SR values (0.52–1.19 mm). The model effectively enhanced positional linearity and improved imaging system UFOV from approximately 10% to over 90% compared to the classical Anger algorithm. Edge spatial resolution was effectively improved and maintained consistency with the central region.

Furthermore, MURA system imaging performance using the CNN model improved significantly, with reconstructed image SNR 5.92 times greater than the TCOG-0.005 algorithm. The CNN γ-ray localization model demonstrated substantial generalization capabilities across energy and crystal thickness in thick continuous crystal imaging systems, significantly improving image SNR and showing considerable development potential.

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Author Contributions

All authors contributed to study conception and design. Material preparation, data collection, and analysis were performed by Wei LU, Lei WANG, and Mingzhe LIU. The first draft was written by Wei LU, and all authors commented on previous versions, read, and approved the final manuscript.

Data Availability Statement

The data supporting this study's findings are openly available in Science Data Bank at https://www.doi.org/10.57760/sciencedb.j00186.00287 and https://cstr.cn/31253.11.sciencedb.j00186.00287.

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