

Deep Learning-Based Simultaneous Separation of Overlapping Projection Data and Attenuation and Scatter Correction for Multi-Pinhole SPECT

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Research Article

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Abstract

Objective

Multi-pinhole SPECT offers improved sensitivity and spatial resolution; however, overlapping projection data and multiple sources of physical image degradation remain major challenges. We propose a novel convolutional neural network (CNN)-based framework that simultaneously separates overlapping projections and corrects for gamma-ray attenuation, scatter, quantum noise, and aperture effects without requiring an attenuation coefficient map (μ -map) derived from X-ray CT.

Methods

Brain imaging was investigated using a three-detector stationary SPECT system equipped with a 44-pinhole collimator (pinhole diameter, 2 mm). A U-Net++-based CNN was trained to separate overlapping projections and correct multiple physical degradation factors. The input comprised overlapping projection data generated by Monte Carlo photon transport simulations, whereas the target data were ideal projections calculated using a ray-tracing method without projection overlap, attenuation, scatter, or other physical effects. A publicly available brain image dataset comprising 30 cases was used for training (2,520 images) and testing (30 images). Corrected projections were reconstructed using the maximum-likelihood expectation-maximization (ML-EM) method. Image quality was evaluated visually and quantitatively using the normalized mean squared error (NMSE), peak signal-to-noise ratio (PSNR), and structural similarity index measure (SSIM). One-sided t-tests were performed against images reconstructed with 11 non-overlapping pinholes, a fan-beam collimator, and the conventional Moore correction method.

Results

The proposed framework accurately separated overlapping projections and simultaneously suppressed attenuation, scatter, quantum noise, and aperture-related degradation. It also reduced artifacts caused by the limited number of projections. The proposed method achieved an NMSE of 0.18 ± 0.02 , a PSNR of 18.38 ± 0.79 dB, and an SSIM of 0.81 ± 0.04 , outperforming 11-pinhole reconstruction (NMSE, 0.24 ± 0.06 ; PSNR, 15.54 ± 1.35 dB; SSIM, 0.76 ± 0.09) and fan-beam reconstruction (NMSE, 0.20 ± 0.03 ; PSNR, 15.93 ± 1.12 dB; SSIM, 0.78 ± 0.05).

Conclusions

The proposed CNN-based framework enables simultaneous projection separation and correction of multiple physical degradation factors in stationary multi-pinhole SPECT without CT-derived attenuation correction. This approach may reduce radiation exposure and system cost while enabling high-sensitivity, high-resolution, and quantitatively accurate SPECT imaging.

Introduction

In clinical single-photon emission computed tomography (SPECT), parallel-hole or fan-beam collimators are generally used for gamma-ray detection, and projection data are acquired by rotating the gamma camera around the subject. In contrast, pinhole collimators can achieve high spatial resolution through magnified projection and have therefore been primarily used for small-animal SPECT [1]. Because pinhole collimators have relatively low gamma-ray detection efficiency and require prolonged acquisition times to obtain tomographic images, multiple pinholes are typically arranged on a cylindrical surface to increase detection efficiency [2]. Such systems, exemplified by U-SPECT, can improve both sensitivity and spatial resolution [3], leading to the development of high-resolution clinical SPECT systems based on similar geometries [4, 5]. In addition, stationary head SPECT systems with a helmet-shaped configuration and multiple pinholes have been proposed [6]. These systems can dramatically reduce acquisition time and are expected to serve as next-generation dynamic SPECT systems capable of capturing temporal information [7].

However, several challenges remain in the practical implementation of stationary data-acquisition systems. The first is the limited number of projections resulting from the fixed arrangement of the pinholes and detectors. Because the positions and angular directions from which projection data are acquired are restricted, reconstructed images may contain artifacts compared with conventional reconstruction using projections acquired over a wide range of angles [8, 9]. To address this problem, reconstruction methods based on total variation (TV) regularization [10] have been investigated. More recently, deep learning-based approaches, including correction using a Deep Image Prior [11], missing-data completion using convolutional neural networks (CNNs) [12], and post-processing using generative adversarial networks (GANs) [13], have also been proposed. However, these approaches may compromise the continuity of three-dimensional structures and still face challenges in maintaining quantitative accuracy.

The second major challenge is the overlap of projection data that occurs when the number of pinholes is increased to improve sensitivity. Projection overlap makes the positional information of radioactive sources ambiguous among different pinholes, potentially degrading image quality and quantitative accuracy [9]. A physical shutter used in dedicated brain SPECT systems to avoid projection overlap [14], however, is inherently counterproductive to the goal of increasing sensitivity. Another approach uses a system matrix to separate overlapping projection data [15], but this method is associated with substantial computational costs, amplification of quantum noise, and limitations in the degree of overlap that can be effectively separated. Therefore, a CNN-based separation approach that avoids excessive computational costs while utilizing all acquired data is a promising strategy, although it has not yet been sufficiently investigated.

In addition, physical image degradation caused by photoelectric absorption and Compton scattering of gamma rays remains a critical issue [16]. Accurate quantitative imaging requires attenuation correction using CT images; however, this introduces additional radiation exposure and potential spatial misregistration between SPECT and X-ray CT images [17]. In the PET field, deep learning-based approaches have recently been proposed to address these limitations [18, 19]. For example, Deep-JASC,

which simultaneously performs attenuation and scatter correction using a single CNN [20], and restoration methods for low-dose images [21] have demonstrated that CNNs can provide powerful and rapid correction without requiring CT images. These advances suggest substantial potential for the application of deep learning-based correction to SPECT [22]. Against this background, we propose a novel CNN-based method for separating overlapping projection data, a problem inherent to multi-pinhole SPECT. Furthermore, we propose a unified CNN-based framework that simultaneously corrects for gamma-ray attenuation, scatter, quantum noise, and aperture effects.

Materials and Methods

Proposed Method

In this study, a unified framework based on U-Net ++ was developed to separate overlapping pinhole projection images and simultaneously correct for gamma-ray attenuation, scatter, quantum noise, and blurring caused by the finite pinhole aperture. The workflow and parameters used in the proposed method are shown in Fig. 1.

First, images of the gamma-ray attenuation coefficient distribution and radioactivity distribution were generated from a publicly available database. Two types of projection data were then generated from these images. The first consisted of overlapping pinhole projection data affected by gamma-ray attenuation, scatter, quantum noise, and finite pinhole aperture effects, generated using Monte Carlo photon transport simulations. The second consisted of ideal pinhole projection data calculated using a ray-tracing method, assuming an infinitesimally small pinhole and excluding the effects of attenuation, scatter, quantum noise, and aperture blurring.

For the Monte Carlo photon transport simulations, an in-house code that had been previously validated against the EGS5 code [23, 24] was used. The simulations were accelerated using a graphics processing unit (GPU; NVIDIA A100, 80 GB memory, NVIDIA, USA). For generating the latter projection data, the pinholes were divided into two groups, A and B, and the projection data were calculated separately for each group so that the individual pinhole projections did not overlap. These ideal projection data were used as the target data for CNN training. By training the network using these paired input and target projection data, the network was designed to separate overlapping projection images into non-overlapping projections while simultaneously correcting multiple sources of image degradation, including gamma-ray attenuation, scatter, quantum noise, and blurring caused by the finite pinhole aperture. For downsampling and upsampling in the network, Average Pooling and Unpooling layers were used, respectively. Average Pooling was adopted to suppress the effects of quantum noise.

Simulation Conditions

As shown in Fig. 2(a), a three-detector SPECT system was simulated. The collimator and detectors were positioned 25.0 cm and 32.6 cm, respectively, from the center of the reconstruction volume. The

collimator consisted of a knife-edge pinhole collimator fabricated from a 1-cm-thick tungsten plate, with a pinhole diameter of 2 mm and an acceptance angle of 24° . The central axis of each pinhole was directed toward the center of the reconstruction volume. The pinhole arrangement is shown in Fig. 2(b). To facilitate the separation of overlapping projections, the pinholes were divided into two groups, Group A (red) and Group B (blue). Projection overlap occurred between pinholes belonging to the different groups. Technetium-99m (^{99m}Tc ; 140 keV) was assumed as the radioisotope. The detector was modeled as a NaI(Tl) scintillation detector with an energy resolution of 10% full width at half maximum (FWHM) at 140 keV. The detector consisted of 512×256 pixels with a pixel size of $0.8 \times 0.8 \text{ mm}^2$, and the intrinsic spatial resolution was set to 3.5 mm FWHM. The energy window for data acquisition was set to $140 \text{ keV} \pm 10\%$. The reconstruction volume consisted of $128 \times 128 \times 128$ voxels with a voxel size of $2 \times 2 \times 2 \text{ mm}^3$. In the photon transport simulations, a total activity of 370 MBq of the radiopharmaceutical was assumed to be distributed in the brain. This setting generated projection data with a practical noise level consistent with standard clinical acquisition conditions while incorporating the effects of gamma-ray attenuation and scatter within the body. Image reconstruction was performed using the maximum-likelihood expectation-maximization (ML-EM) algorithm with 100 iterations.

Generation of Brain Phantoms and Projection Data

Because publicly available SPECT/CT datasets are limited, T2-weighted magnetic resonance imaging (MRI) data obtained from publicly available databases [25, 26] were processed and used to generate the brain phantom data. First, because the matrix sizes and slice thicknesses differed among the MRI datasets, all images were resampled using linear interpolation to a uniform matrix size of $128 \times 128 \times 128$ voxels with a voxel size of $2 \times 2 \times 2 \text{ mm}^3$. To generate the radioactivity distribution, contrast enhancement using histogram equalization and thresholding were applied to the MRI images, and the brain was segmented into three regions: white matter, gray matter, and ventricles. Activity values simulating the uptake ratios observed in ^{99m}Tc -HMPAO cerebral blood flow SPECT were assigned to each region, and photon transport calculations were performed using Monte Carlo simulations. The attenuation coefficient map (μ -map) was generated from CT images at the same slice positions as the MRI images. Soft tissue and bone were extracted by thresholding, and linear attenuation coefficients for 140-keV gamma rays of 0.153 and 0.28 cm^{-1} were assigned to the respective regions.

Using these phantoms, a dataset comprising 30 cases was constructed, with 28 cases used for training and 2 cases for testing. For data augmentation of the training dataset, each phantom was tilted relative to the axial axis by four angles ($\pm 15^\circ$ and $\pm 30^\circ$). For each tilted phantom, projection data were generated at 18 angular positions using three detectors with six rotations at 20° intervals. The final dataset comprised 2,520 training images ($28 \text{ cases} \times 5 \text{ tilt angles} \times 18 \text{ angular positions}$) and 30 test images ($10 \text{ cases} \times 3 \text{ angular positions}$).

Comparison with Conventional Methods

To investigate the trade-off between the sensitivity improvement associated with increasing the number of pinholes and image degradation caused by projection overlap, the following conditions were evaluated. First, an 11-pinhole configuration was established in which the individual projection images did not overlap on the detector [27]. The central axis of each pinhole was directed toward the center of the reconstruction volume. Because projection separation was not required under the 11-pinhole condition, U-Net ++ was trained to correct for gamma-ray attenuation, scatter, quantum noise, and aperture effects. This condition served as the baseline for evaluating physical correction. The proposed method primarily employs fully stationary data acquisition, in which projection data are acquired at three angular positions without rotating the detectors. In addition, quasi-stationary data acquisition was investigated, in which the detectors were rotated by 60° once to acquire projection data at six angular positions, to evaluate the reduction of reconstruction artifacts. The total acquisition time was set to 30 s for all stationary and quasi-stationary conditions.

For comparison, rotational data acquisition using a clinically used fan-beam collimator was also implemented. Three detectors were rotated by 3° for 40 steps, resulting in a total of 120 projection directions. The total acquisition time was 600 s, with 5 s of acquisition per projection using a step-and-shoot acquisition scheme. The reconstructed images were compared with those obtained using the proposed method. Furthermore, to compare the proposed method with a previously reported approach, the conventional method proposed by Moore et al. [15], which incorporates projection separation into the iterative reconstruction process, was implemented. Because the Moore method does not incorporate attenuation, scatter, or spatial resolution correction, an attenuation correction term based on the μ -map was added [28]. Scatter correction was performed using the triple-energy-window (TEW) method [29], and detector intrinsic spatial resolution was corrected using a deconvolution method with a point-spread function (PSF) having a full width at half maximum (FWHM) of 3.5 mm. The Moore method was originally developed using multi-pinhole projection data acquired with pinholes arranged on a cylindrical surface. When projection separation is performed using the Moore algorithm under the fully stationary acquisition configuration assumed in the present study, in which the three detectors are fixed at only three angular positions, severe artifacts arise because of the insufficient number of projection directions. Therefore, to demonstrate the practical separation limit of the Moore algorithm as a reference, reconstruction results using projection data acquired at 18 angular positions are presented. In contrast, the proposed method reconstructs images from projection data acquired at only three or six angular positions.

Evaluation Methods

In this study, quantitative evaluation was performed using three evaluation metrics: normalized mean squared error (NMSE), peak signal-to-noise ratio (PSNR), and structural similarity index measure (SSIM). These metrics were calculated for both the projection data and all slices of the reconstructed three-dimensional images. The statistical significance of the effectiveness of the proposed method was evaluated using a one-sided *t*-test.

Results

Separation of Overlapping Projection Data

Figure 3 shows the CNN input images, CNN output images, and intensity profiles along the green line in the output image of pinhole group A and the corresponding ground-truth image for the 44-pinhole configuration, in which projection overlap occurred. In the input image shown in Fig. 3(a), the effects of projection overlap are apparent, with individual pinhole projections superimposed on each other. In contrast, the CNN output images in Figs. 3(c) and 3(d) demonstrate that the projection data from pinhole groups A and B were successfully separated. Furthermore, the high degree of agreement between the intensity profiles shown in Fig. 3(b) indicates that the CNN achieved accurate separation of the overlapping projections.

Table 1 summarizes the errors between the separated projection data and the ground truth, the total number of counts, and the counts per angular position. Statistical analysis revealed a significant difference in the PSNR of the projection data between the 11-pinhole condition (fully stationary data acquisition) and the 44-pinhole conditions (both fully stationary and quasi-stationary data acquisitions) ($p = 0.05$).

Evaluation of Reconstructed Images

Figure 4 shows a comparison of the reconstructed images. Figure 4(a) shows the ground-truth radioactivity distribution, and Fig. 4(b) shows the corresponding μ -map. Figure 4(c) presents the reconstructed image obtained using rotational data acquisition with a fan-beam collimator. Figure 4(d) shows the reconstructed image obtained using the 11-pinhole configuration with fully stationary data acquisition. Figure 4(e) shows the reconstructed image after correction using the Moore method (2-mm-diameter pinholes with data acquisition at 18 angular positions). Figure 4(f) shows the reconstructed image obtained using the proposed method with 2-mm-diameter pinholes and projection data acquired at three angular positions (fully stationary data acquisition). Figure 4(g) shows the reconstructed image obtained using the proposed method with projection data acquired at six angular positions (quasi-stationary data acquisition), in which data were acquired after a single 60° rotation of the detectors. The corresponding absolute error images relative to the ground truth are also presented for each reconstruction method. In the visual comparison, the reconstructed image obtained using rotational data acquisition with the fan-beam collimator (Fig. 4(c)) showed excellent reproducibility of the internal brain structures because of the large number of acquisition directions. However, the influence of quantum noise due to insufficient detected photons was apparent. In the 11-pinhole fully stationary acquisition (Fig. 4(d)), image degradation caused by projection overlap was avoided; however, noticeable artifacts resulting from the insufficient number of projection angles were observed. The reconstructed image obtained using the Moore method with 18 angular positions (Fig. 4(e)), which was implemented as a reference based on previous research, exhibited considerable blurring throughout the image. In contrast,

the proposed method using the 44-pinhole fully stationary acquisition (Fig. 4(f)) increased the number of projection data owing to the larger number of pinholes, resulting in suppression of quantum noise and reconstruction artifacts. Furthermore, the reconstructed image obtained with quasi-stationary data acquisition (Fig. 4(g)) showed additional reduction of the artifacts observed in Fig. 4(f). The anatomical structures of the gray matter and white matter became closer to those of the ground-truth image shown in Fig. 4(a).

Table 1 summarizes the NMSE, PSNR, and SSIM values of the reconstructed images. Statistical analysis demonstrated that the PSNR of the reconstructed images obtained using the 44-pinhole configuration with quasi-stationary data acquisition was significantly higher than that of all other reconstruction methods ($p = 0.05$).

Discussion

The proposed method successfully separated the overlapping projection data from the 44-pinhole configuration into individual pinhole projections. Quantitative evaluation of the reconstructed images demonstrated that the errors were comparable to those obtained with the 11-pinhole condition, where projection separation was not required. Furthermore, increasing the number of pinholes improved the artifacts caused by insufficient projection data observed in the 11-pinhole condition. These artifacts were almost completely eliminated when six angular positions obtained by quasi-stationary data acquisition were used.

In this study, the acquisition time for fully stationary data acquisition was set to 30 s, assuming a total activity of 370 MBq accumulated in the brain. Under this condition, the maximum count in a pinhole projection image was approximately 50 counts. Since high-quality SPECT images could be reconstructed even with this low count level, the proposed method may be applicable to clinical conditions in which the brain uptake is approximately 80 MBq. In such a case, extending the acquisition time by a factor of five to 150 s would provide sufficient counts for clinical application. Furthermore, even with quasi-stationary data acquisition, the total acquisition time would remain approximately 5 min. For comparison with currently used clinical fan-beam SPECT acquisition, we simulated rotational acquisition with 120 projection directions and a total acquisition time of 600 s (5 s per projection). Although this approach did not produce artifacts caused by insufficient angular sampling, the reconstructed images were affected by quantum noise due to the limited detected counts. Suppression of this noise resulted in image blurring. In the present simulation, effects such as collimator septal penetration and septal thickness were not considered; therefore, the actual number of detected photons in experimental projection data is expected to be lower. Although pinhole collimators generally have lower geometric efficiency than fan-beam collimators, their sensitivity can be sufficiently improved by using multiple pinholes.

The major advantage of the proposed method is that it enables separation of overlapping projection data using a CNN, allowing the projection magnification on the detector surface to be increased to improve spatial resolution while simultaneously enhancing sensitivity through the use of multiple pinholes.

Another important advantage of the proposed framework is that attenuation, scatter, quantum noise, and aperture effects are corrected directly by the CNN. Therefore, image reconstruction can be performed using the ML-EM algorithm without incorporating additional correction terms into the reconstruction process to explicitly model these physical degradation factors. This feature simplifies the reconstruction procedure and demonstrates the potential of the proposed approach for practical high-sensitivity and high-resolution stationary multi-pinhole SPECT imaging.

Because no previous method with an approach similar to the proposed framework has been reported for correcting the effects of overlapping projection data, the method proposed by Moore et al. [15] was implemented as a reference method in this study. The Moore method incorporates a probabilistic model of projection overlap into the system matrix to perform correction during iterative reconstruction. However, when applied to fully stationary acquisition data with only three angular positions, as assumed in the present study, the method suffers from increased artifacts due to insufficient angular sampling and increased quantum noise. Although filtering can be applied to suppress these artifacts, this inevitably reduces the spatial resolution of the reconstructed images. Consequently, as shown in Fig. 4(e), the correction performance of the Moore method was limited under the acquisition conditions evaluated in this study.

Regarding scatter and attenuation correction, the triple-energy-window (TEW) method [29] has been widely used for conventional scatter correction. However, this method has the disadvantage that quantum noise remains significant in projection data, particularly under low-count conditions. For attenuation correction in heterogeneous media, CT-based correction methods are currently the standard approach. Although these methods provide highly accurate reconstructed images, they require SPECT/CT systems, resulting in increased system cost and additional radiation exposure to patients. Furthermore, spatial misregistration between CT and SPECT images caused by respiratory motion or patient movement may introduce artifacts into the corrected images [17]. In the PET field, advanced deep learning-based approaches, such as Deep-JASC [20], which simultaneously performs attenuation and scatter correction, have been proposed, including CT-free attenuation correction methods. However, these approaches are primarily designed for reconstructed PET images and are difficult to directly apply to SPECT projection data, which have different physical characteristics. In contrast, the proposed method addresses these issues by training U-Net ++ using ideal projection data generated by ray tracing as target data, enabling correction of gamma-ray attenuation and scatter effects at the projection-data level before image reconstruction. Because the proposed method does not require CT images, it eliminates additional radiation exposure and avoids the risk of artifacts caused by SPECT/CT misregistration. Moreover, the proposed framework successfully addresses not only conventional physical degradation factors, including attenuation, scatter, quantum noise, and aperture blurring, but also the unique challenge of separating overlapping projection data in multi-pinhole SPECT. As a result, reconstructed images can be obtained using a conventional ML-EM reconstruction process without additional CT acquisition or complicated hardware modifications. This approach has the potential to reduce system cost while substantially improving quantitative accuracy. Furthermore, for geometric blurring caused by the finite pinhole aperture, conventional approaches require accurate system matrix

calculations with high computational costs, such as those based on the Siddon method [30, 31]. In the proposed method, this issue is addressed by using ideal projection data generated through ray tracing as training targets, thereby avoiding the need for computationally intensive system matrix calculations.

Regarding the separation accuracy of projection data, a significant difference was observed only in the PSNR metric between the 11-pinhole fully stationary acquisition and the 44-pinhole fully stationary and quasi-stationary acquisitions, with the 11-pinhole condition showing superior performance ($p = 0.05$). This result may be attributed to the fact that projection separation was not required in the 11-pinhole condition, making the learning task simpler and resulting in improved separation accuracy.

For the reconstructed images, the 44-pinhole quasi-stationary acquisition achieved significantly higher PSNR values than all other methods, including fan-beam reconstruction, 11-pinhole fully stationary acquisition, and 44-pinhole fully stationary acquisition ($p = 0.05$). In addition, for NMSE, the 44-pinhole quasi-stationary acquisition maintained an error level comparable to that of the fan-beam reconstruction while significantly reducing the error compared with the Moore method, 11-pinhole fully stationary acquisition, and 44-pinhole fully stationary acquisition ($p = 0.05$). These improvements are likely due to the increased number of photon detection directions provided by the larger number of pinholes, which reduced reconstruction artifacts and improved the quantitative accuracy of the reconstructed images.

In this study, the proposed method was evaluated for brain SPECT imaging. Considering the anatomical characteristics of the brain, the major attenuating structures are limited primarily to the brain tissue and skull. Therefore, variations among patients in the attenuation distribution are relatively small, and the attenuation and scatter models learned by the CNN were considered to function effectively. In contrast, for other applications such as myocardial imaging, the attenuation distribution includes regions with substantially different attenuation coefficients, such as soft tissue, bone, and air. Therefore, the current workflow of the proposed method may not be directly applicable to such organs. However, as demonstrated in our previous study [32], μ -maps can be estimated from low-energy gamma-ray data acquired using lower energy windows in SPECT. Therefore, an extended approach incorporating such estimated μ -maps may enable application of the proposed framework to other organs with more complex attenuation distributions. Future studies will investigate the effectiveness of the proposed method using clinical patient data and evaluate its potential for extension to imaging of other organs.

Conclusion

In this study, we proposed a method for a three-detector multi-pinhole SPECT system that simultaneously performs projection overlap separation and correction of physical image degradation using U-Net++, and evaluated its performance. The results demonstrated that overlapping projections generated by the 44-pinhole configuration could be successfully separated into individual pinhole-group projections using the CNN. Furthermore, the proposed method was able to learn the effects of gamma-ray attenuation and scatter within the body and achieve simultaneous physical correction without requiring an attenuation coefficient map (μ -map).

Declarations

Conflict of interest

The authors declare no potential conflicts of interest.

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Data availability

The data used and analyzed during the current study are available from the corresponding author on reasonable request.

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Table 1

Table 1 is available in the Supplementary Files section.

Figures

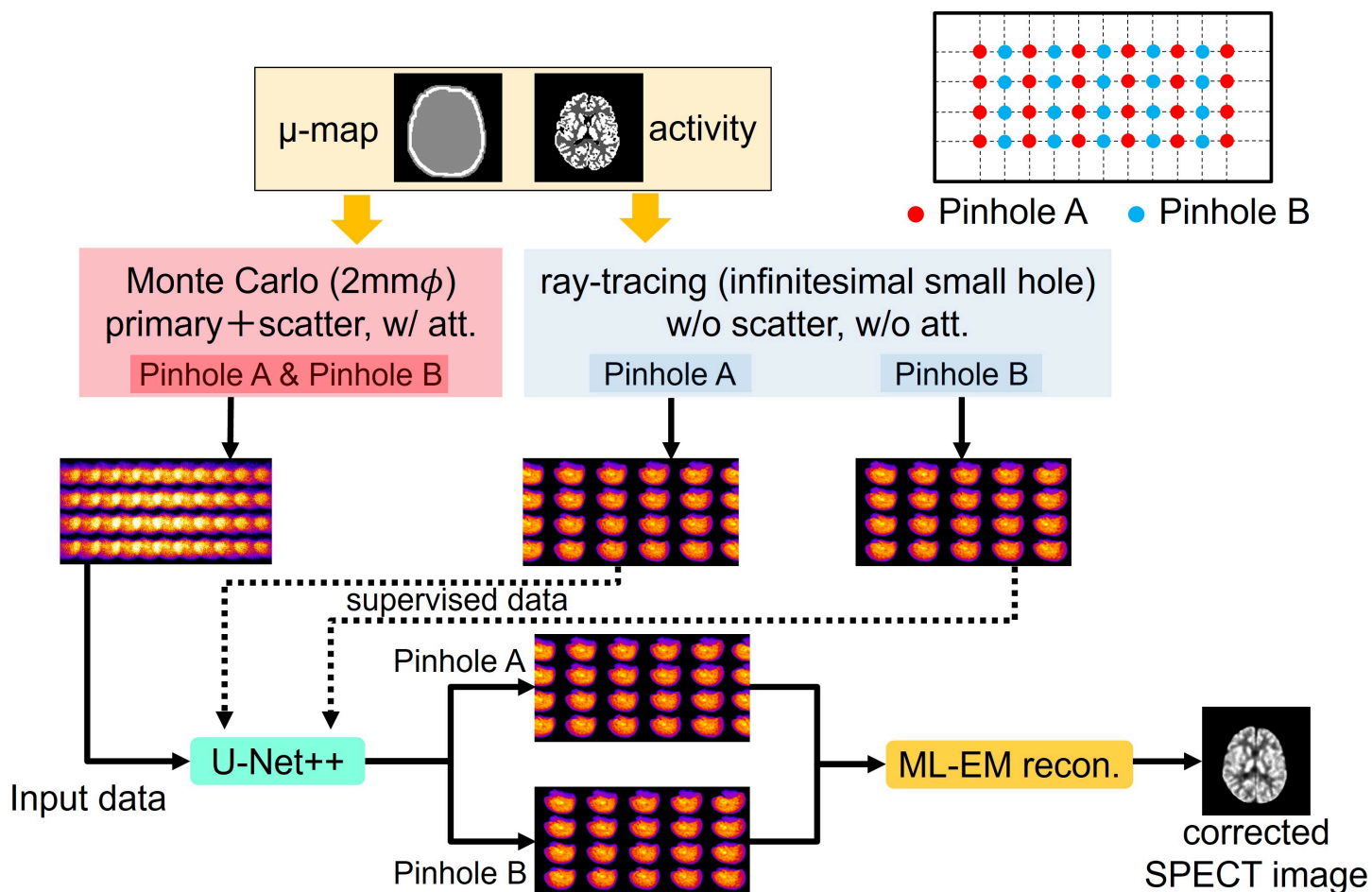


Figure 1

Workflow of the proposed method.

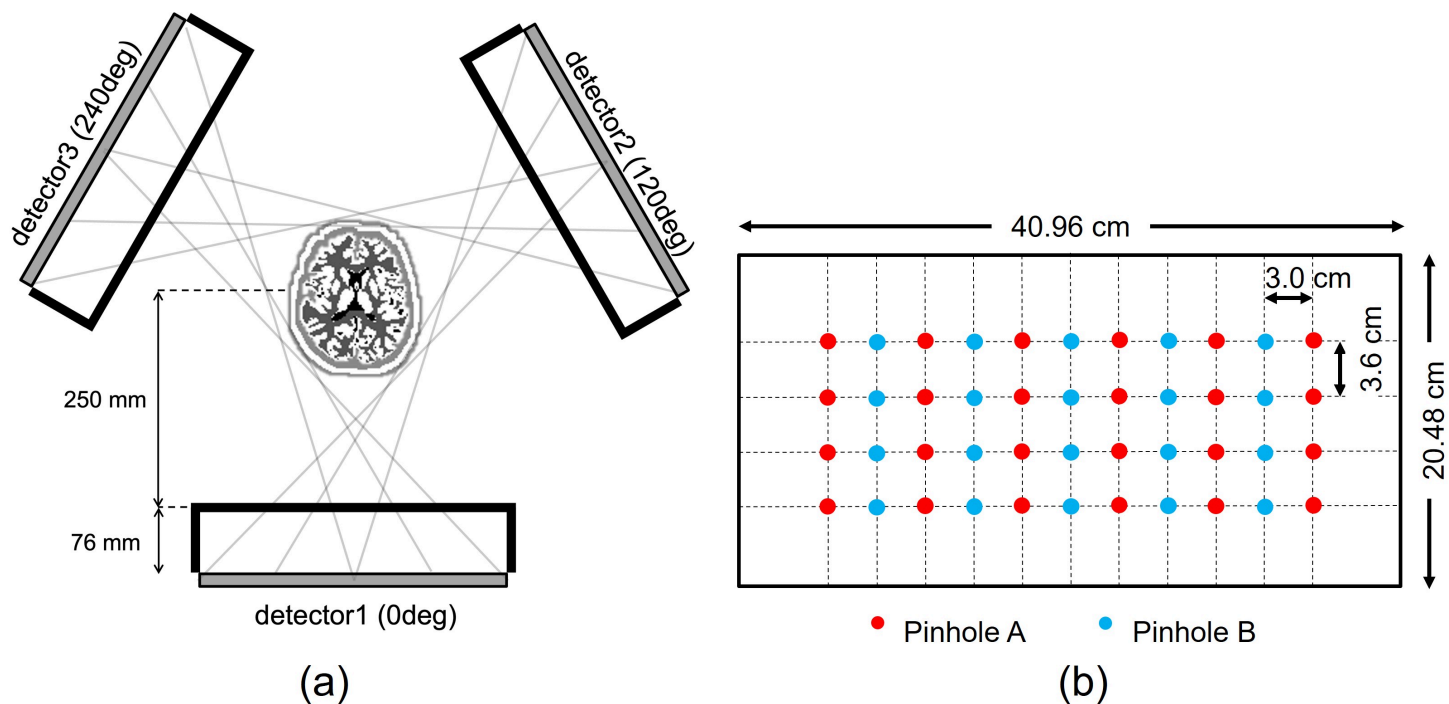


Figure 2

Simulation geometry. (a) Detector arrangement and (b) pinhole arrangement.

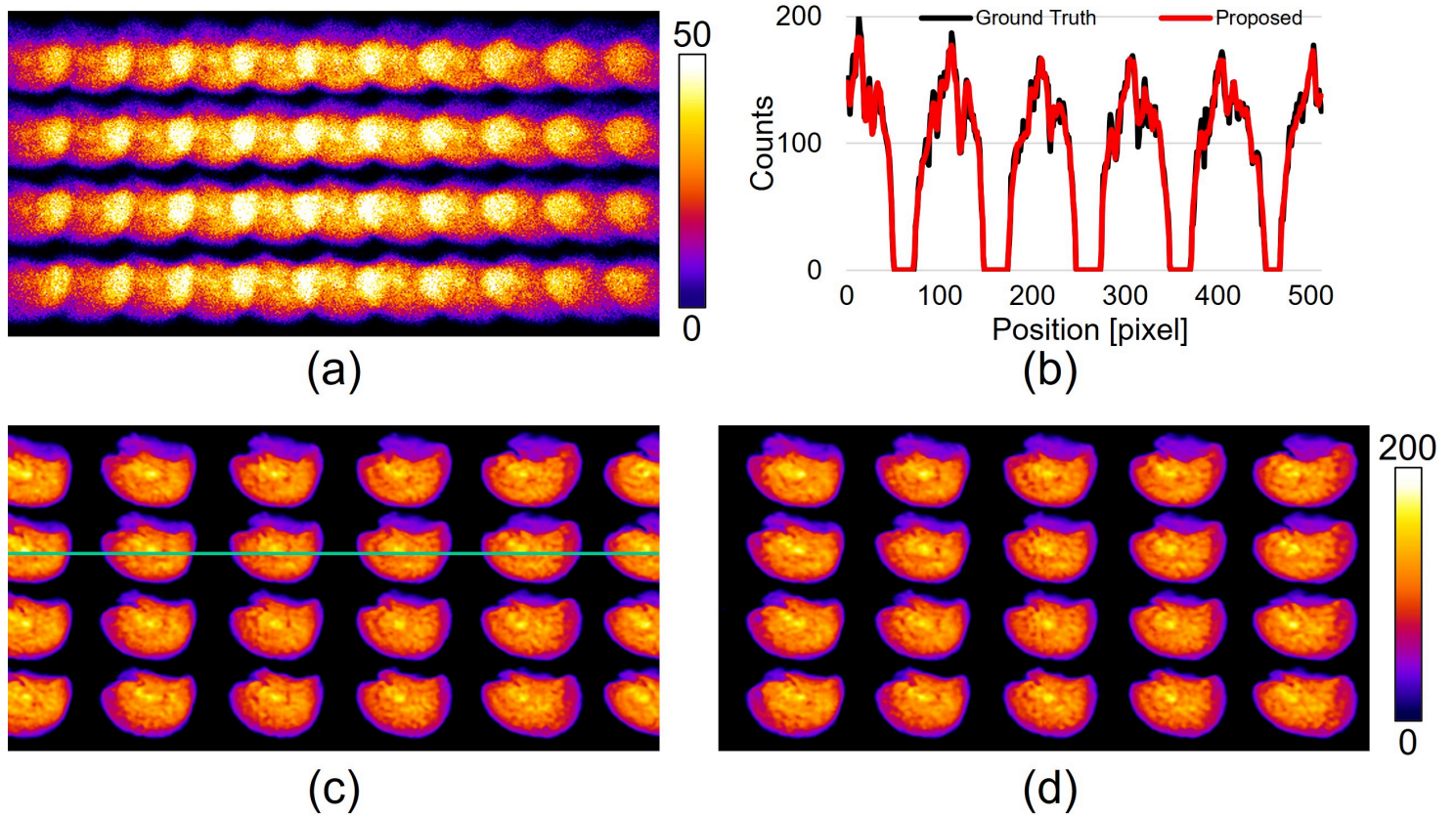


Figure 3

Separation of overlapping projection data. (a) Overlapping projection data, (b) intensity profiles of the separated projection data and the ground-truth projection data, (c) separated projection data from pinhole group A, and (d) separated projection data from pinhole group B.

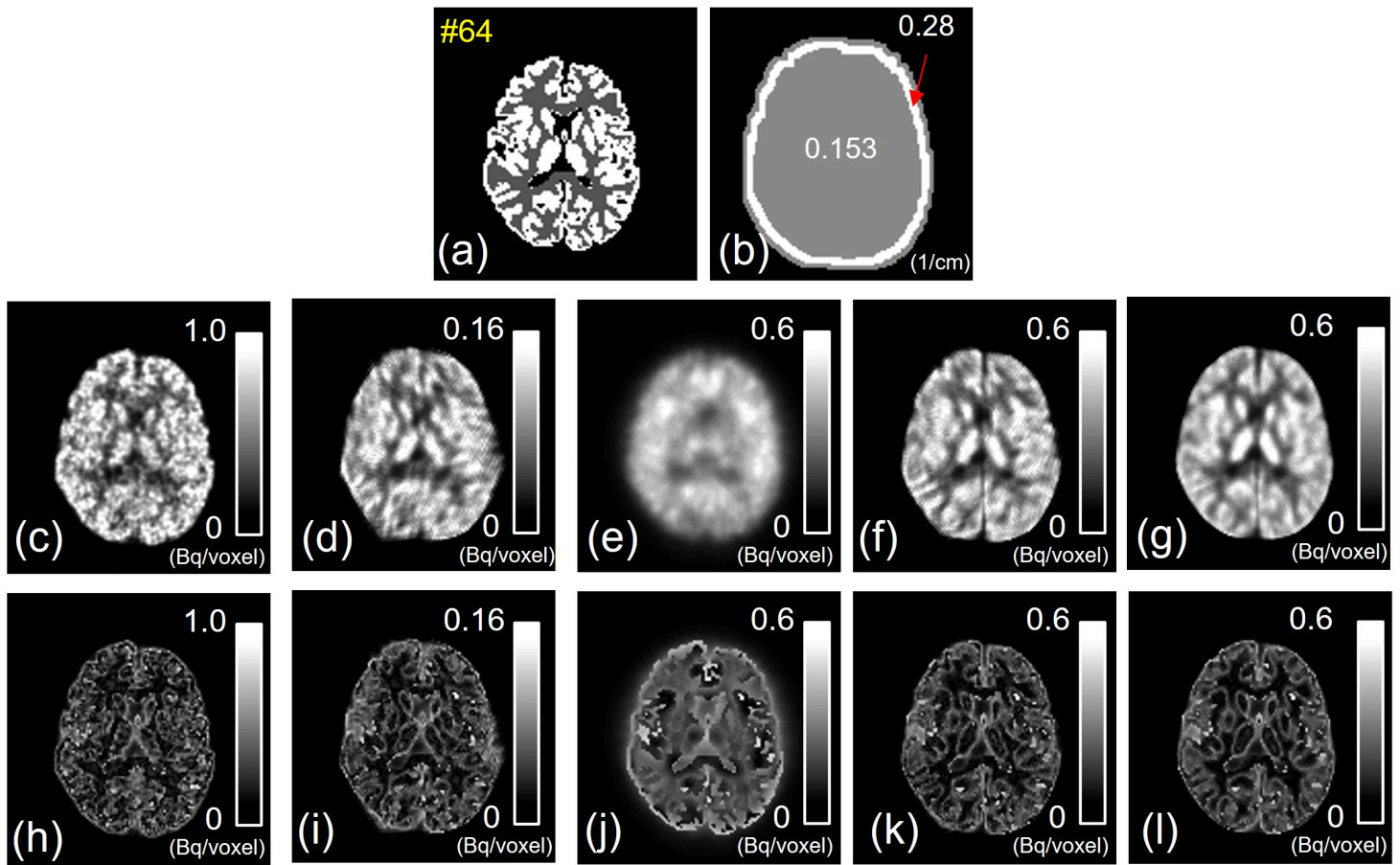


Figure 4

Comparison of reconstructed images. (a) Radioactivity distribution (ground truth), (b) μ -map, (c) reconstructed image from fan-beam data acquisition, (d) reconstructed image from 11-pinhole (2-mm diameter) fully stationary data acquisition, (e) reconstructed image corrected using the Moore method, (f) reconstructed image from 44-pinhole (2-mm diameter) fully stationary data acquisition, (g) reconstructed image from 44-pinhole (2-mm diameter) quasi-stationary data acquisition, and (h-l) absolute error images between the reconstructed images in (c-g) and the ground-truth image in (a).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [table11.xlsx](#)