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Primary Hip

Measurement of the Acetabular Cup Orientation After Total Hip Arthroplasty Based on 3-Dimensional Reconstruction From a Single X-Ray Image Using Generative Adversarial Networks



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ABSTRACT

Background: The purpose of this study was to reconstruct 3-dimensional (3D) computed tomography (CT) images from single anteroposterior (AP) postoperative total hip arthroplasty (THA) X-ray images using a deep learning algorithm known as generative adversarial networks (GANs) and to validate the accuracy of cup angle measurement on GAN-generated CT.

Methods: We used 2 GAN-based models, CycleGAN and X2CT-GAN, to generate 3D CT images from X-ray images of 386 patients who underwent primary THAs using a cementless cup. The training dataset consisted of 522 CT images and 2,282 X-ray images. The image quality was validated using the peak signal-to-noise ratio and the structural similarity index measure. The cup anteversion and inclination measurements on the GAN-generated CT images were compared with the actual CT measurements. Statistical analyses of absolute measurement errors were performed using Mann–Whitney *U* tests and nonlinear regression analyses.

Results: The study successfully achieved 3D reconstruction from single AP postoperative THA X-ray images using GANs, exhibiting excellent peak signal-to-noise ratio (37.40) and structural similarity index measure (0.74). The median absolute difference in radiographic anteversion was 3.45° and the median absolute difference in radiographic inclination was 3.25°, respectively. Absolute measurement errors tended to be larger in cases with cup malposition than in those with optimal cup orientation.

Conclusions: This study demonstrates the potential of GANs for 3D reconstruction from single AP postoperative THA X-ray images to evaluate cup orientation. Further investigation and refinement of this model are required to improve its performance.

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Precise placement of the acetabular cup is essential in total hip arthroplasty (THA), as cup malposition has been identified as a risk factor for postoperative complications such as dislocation, wear, loosening, and impingement [1–5]. Accurate assessment of the acetabular cup orientation is crucial for evaluating the postoperative outcomes of THA.

Angle measurements of cup implants are primarily performed using 2-dimensional (2D) X-ray images because they are widely available, cost-effective, and have low radiation exposure [6–8].

However, the appearance of the pelvic bones on radiographs varies greatly depending on the patient's posture at the time of examination, potentially leading to significant measurement errors [9,10]. Moreover, measurement errors in cup versions often result from difficulties in identifying the cup rim [11,12]. In contrast, recent studies have suggested that computed tomography (CT) measurements should be the gold standard because they are not affected by pelvic posture and are more accurate than radiography [13–15]. In addition, we can easily grasp the positional relationship between the bone and the implant using 3-dimensional (3D) CT. Nonetheless, CT is comparatively more expensive and has a higher radiation exposure, making X-rays the preferred clinical option for evaluation [6,7,16]. Therefore, a technique for estimating 3D CT from 2D X-ray images is desirable. It is believed that this technique can combine the advantages of both the low-cost and low-radiation exposure of X-rays and the accuracy of CT.

A technique that predicts 3D shapes from 2D images, 2D–3D reconstruction, has been studied in the field of computer vision for decades [17]. Although 3D reconstruction from X-ray images has also been studied recently, it is more challenging because X-ray images differ from ordinary images in that, for the purpose of observing the inside of the body, intraobject structures are projected transparently, and each pixel reflects information not only on the body surface but also inside the body [18]. In recent years, deep learning–based 3D reconstruction from X-ray images has been studied [16,18–21]. However, there are no reports on deep learning–based 3D reconstruction of the hip region.

In this paper, we propose a generative artificial intelligence (AI)-based 3D reconstruction system that utilizes generative adversarial networks (GANs), one of the deep learning algorithms, to generate 3D CT images of the hip from single anteroposterior (AP) postoperative X-ray images of THA. To assess the clinical applicability of this system, we validated the accuracy of cup angle measurements on CT images generated using the GAN (Figure 1).

Patients and Methods

The pipeline of the proposed deep learning–based 3D reconstruction system is illustrated in Figure 2. The system comprises 4 steps: preprocessing, training, prediction, and validation. During the Training and Prediction steps, 3D CT images were generated from the X-ray images using 2 GAN models: CycleGAN [22] and X2CT-GAN [20]. Owing to the difficulty of directly reconstructing 3D CT images from X-ray images, we first employed X2CT-GAN to generate 3D CT images from digitally reconstructed radiograph (DRR) images. The DRR is a 2D-simulated image generated from CT data by casting rays [23], and this process is implemented during the preprocessing step. Although the DRR images resemble real X-rays, there is a gap between them. To address this issue, CycleGAN was utilized to translate actual X-ray images into DRR-like images.

By combining both models, 3D CT images were generated from the X-ray images. It is important to note that during the training phase, X-ray, CT, and DRR image data were used, whereas, during the prediction phase, only the X-ray input was required.

Dataset

The study protocol was approved by the institutional review board of our institution.

We retrospectively collected pairs of postoperative AP pelvic radiographs and CT images of 386 patients who underwent primary THAs using a cementless cup (AHFIX Q3; KYOCERA Corporation, Kyoto, Japan) at our institution between March 11, 2015, and November 9, 2022. There were 332 women (86%) and 54 men (14%), who had a median age of 70 years (range, 17 to 89) at the time of surgery. The large proportion of women reflects that patients who have osteoarthritis in Japan are mainly women, secondary to the developmental dysplasia of the hip. Patient data were randomly divided into 309 (80%) and 77 cases (20%) for training and test data, respectively. We used 522 CT and 2282 X-ray images from 309 patients as the training dataset. We routinely perform postoperative CT scans, generally conducted 1 year postoperatively. Computed tomography (CT) volumes and radiographs taken within 1 year after surgery were used. For the test data, the timing of the CT and X-ray images was the same as that of the training dataset. The difference in examination time between the original CT and X-ray images for the prediction of the generated CT image was less than 1 year. To prevent metal artifacts from reducing the quality of the training data, we used only CT images with single-energy metal artifact reduction, which is a raw data–based technique that reduces metal artifacts. Only cases without information on complications, such as loosening, dislocation, or infection, in the electronic medical records were included in this study. There were no missing data since all selected patients had both CT and X-ray images. Personal information was anonymized in the process of extracting image data.

Preprocessing

The CT and X-ray image datasets were normalized using Python 3.7.5 (Python Software Foundation, Beaverton, OR).

Computed Tomography (CT) Standardization

Foreign bodies external to patients in CT images, such as CT tables, were removed because they were considered to negatively impact training as noise. Because the CT pixel values in the implant area were significantly higher than those in other areas, all areas with a maximum pixel value of 1,024 or more were converted to 1,024, and the pixel value range was adjusted between –1,024 and 1,024. For each CT scan, we identified a slice containing the center of

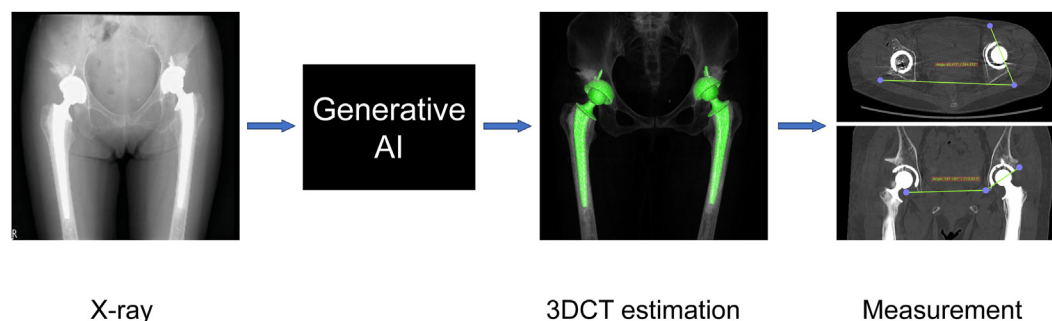


Fig. 1. The concept of this study. AI, artificial intelligence; 3D CT, 3-dimensional computed tomography.

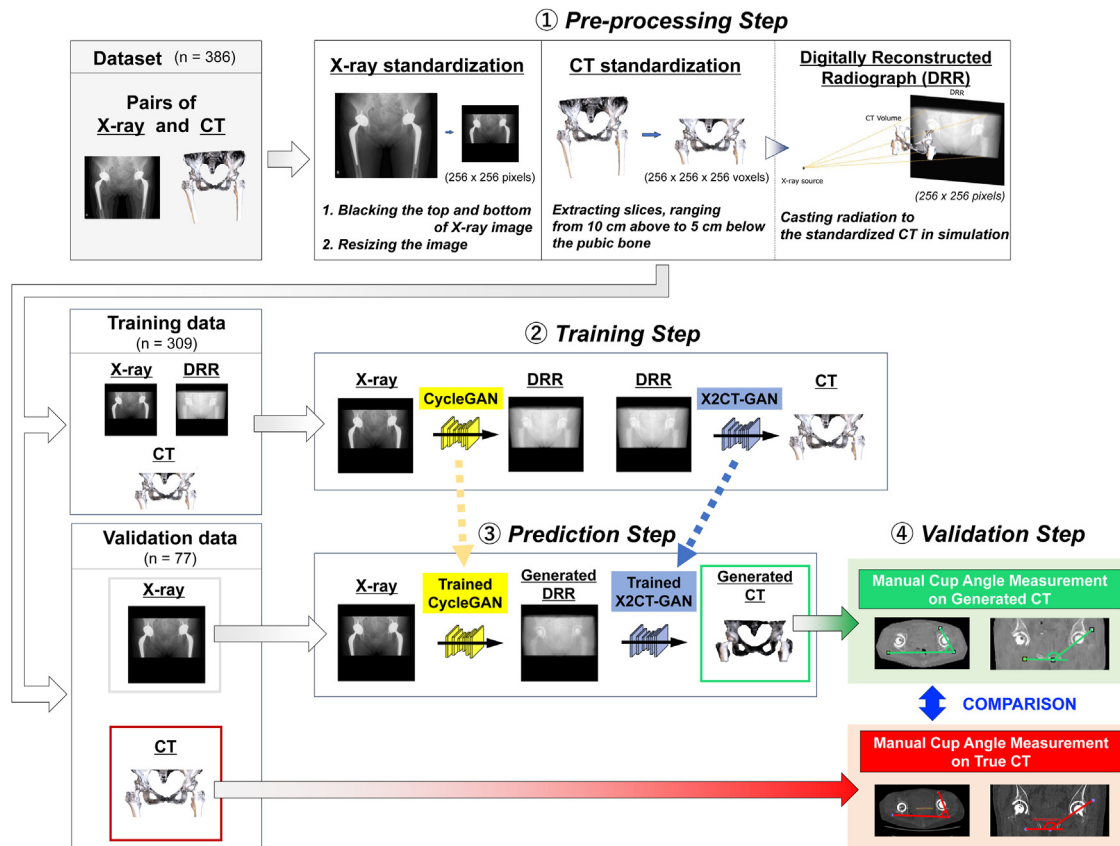


Fig. 2. The overview of this study. CT, computed tomography; DRR, digitally reconstructed radiograph; GAN, generative adversarial network.

the pubic bone in all axial slices and extracted slices ranging from 10 cm proximal to 5 cm distal to the slice (Figure 3A). The original CT data showed a slice thickness of 1.0 or 0.5 mm. The slice thickness was interpolated to divide the 15 cm into 256 slices. Finally, the CT images were resized to $256 \times 256 \times 256$ voxels for a voxel size of $1.366 \times 1.366 \times 0.586$ mm.

Digitally Reconstructed Radiograph (DRR)

We used the open-source software Plastimatch to generate DRR images from the extracted CT volumes [24] (Figure 3B). The DRR images were resized from $2,845 \times 3,408$ pixels to 256×256 pixels.

X-Ray Standardization

The X-ray images were processed to resemble the DRR images to efficiently train the model used in this study (Figure 3C). The pubic symphysis was identified, and the image was translated such that the symphysis was at the center of the screen. The upper and lower areas of the image were processed in black, such that the processed X-ray images were similar to the DRR images. Finally, the X-ray images were resized from $2,845 \times 3,408$ to 256×256 pixels.

Training

We used 2 GAN models: CycleGAN [22] and X2CT-GAN [20]. The workflow of the training models is illustrated in Figure 4. The GAN network structure consists of 2 networks, the “Generator” and the “Discriminator,” which function competitively to improve accuracy [25]. The “Generator” produces new images, and the

“Discriminator” discerns between the generated images and the real images. These 2 networks competed to improve the accuracy of the generated images. Training was conducted using the PyTorch (v1.13.0, running on CUDA 11.6) Python framework. The parameters of the models were randomly initialized according to a normal distribution.

(1) CycleGAN [22].

The CycleGAN was trained using 2282 X-ray images and 522 DRR images for a total of 200 epochs.

(2) X2CT-GAN [20].

The single AP view X-ray input model was used for its usability in actual clinical practice because lateral view X-rays are taken in various ways and are not always taken. The size of the training dataset increased 3-fold with horizontal and vertical flip augmentation. Finally, we trained the X2CT-GAN using 1,566 pairs of CT images and the corresponding DRR images for a total of 250 epochs.

Prediction: Creating “Generated CT”

In this study, we used the peak signal-to-noise ratio (PSNR) and structural similarity index measure (SSIM) [26] to evaluate the quality of the generated images. The PSNR measures the pixel-wise difference between the generated and ground-truth images, with higher values indicating better quality. By contrast, SSIM considers

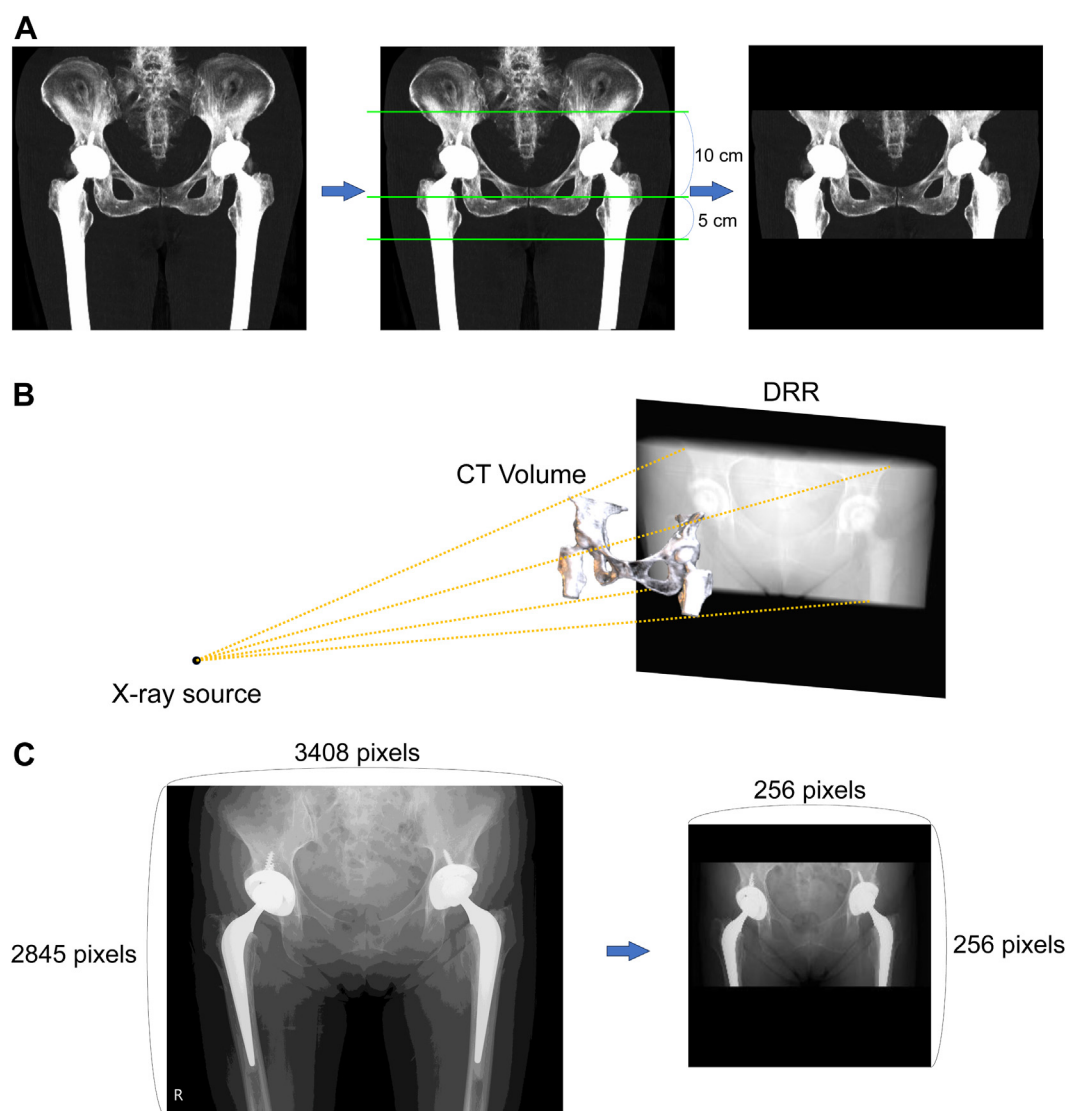


Fig. 3. Three main image preprocessing steps. (A) Extracting CT volumes, ranging from 10 cm above to 5 cm below the center of the pubic bone. (B) Generating DRR images by casting radiation to CT volumes in simulation. (C) Blacking the top and bottom of X-ray images and resizing it. CT, computed tomography; DRR, digitally reconstructed radiograph.

both pixel values and other information, including brightness, contrast, and structure. A higher SSIM value indicates that the generated images are perceptually similar.

Validation: Manual Cup Angle Measurement

In this study, cup alignment was measured on CT data concerning the functional pelvic coordinate system. Murray proposed 3 methods to define cup orientation: radiographic, anatomical, and operative [27]. Cup orientation measured on AP radiographs was defined as radiographic inclination and anteversion (RI and RA). However, when measured on CT, they correspond to RI and anatomical anteversion (AA). Since in most previous studies cup angles were measured using a radiographic definition, the angles from CT should be evaluated using the same definition. Therefore, we converted AA to RA using trigonometric conversion formulas [27]. To assess the accuracy of the measurements on the generated CT, we compared the RI and converted RA measurements on the true CT (true RI and RA) with those on the generated CT (generated

RI and RA). Test data were available for 77 cases, and measurements were obtained for 100 hips.

Data Analyses

The differences between the true RI and generated RI and between the true RA and generated RA were measured. The correlation between the absolute differences in RI and true RI and the absolute differences in RA and true RA was evaluated using nonlinear regression analysis. In addition, we divided the test data of the 100 hips into 2 groups based on whether the absolute difference exceeded 10° . For both groups, we calculated the difference between the median true RI value and each true RI value, and the differences were compared using the Mann–Whitney *U* test. The same process was applied to the RA. Box plots were created, and the data were presented as the median and interquartile range (IQR). All analyses were performed using Python version 3.7.5.

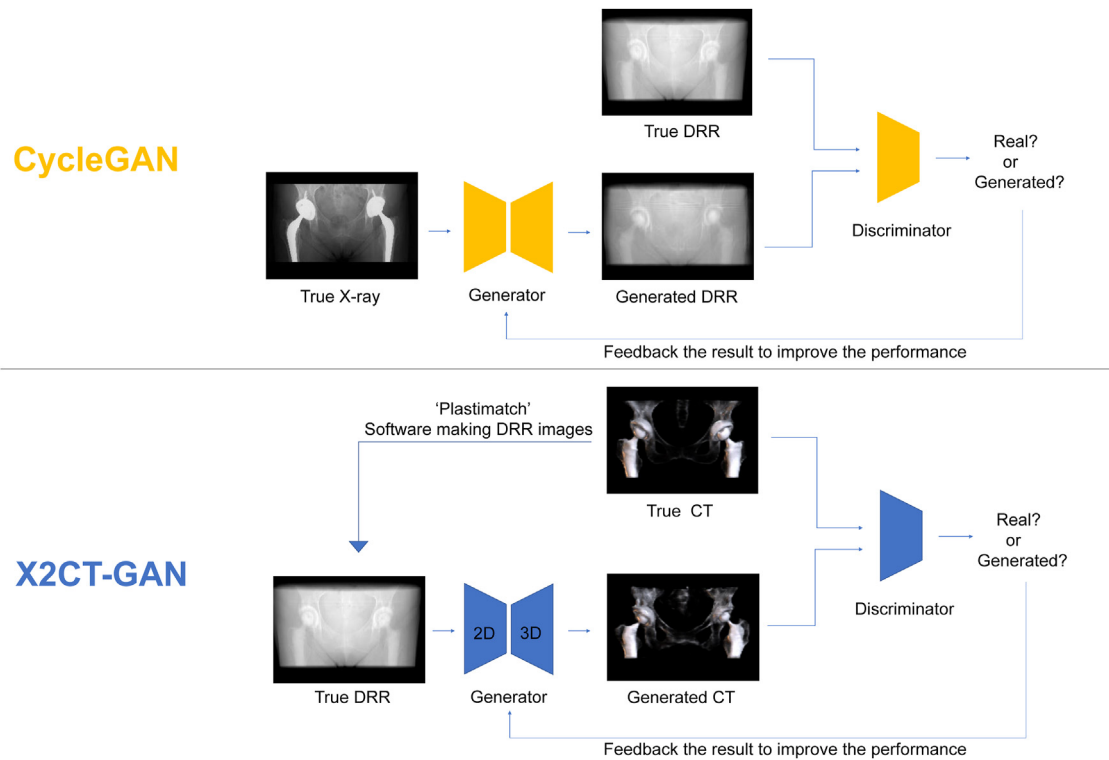


Fig. 4. The workflow for training models.

Results

Three-dimensional (3D) CT Generation from X-Ray Images

We successfully generated 3D CT from single AP hip post-operative X-ray images. Figure 5 shows an example of the true and generated 3D CT of the same patient.

In this model, we achieved excellent PSNR (37.40) and SSIM (0.74), which are better than the values reported in the original paper.

Cup Angle Measurement

In the true CT group, the median AA (and IQR) was 27.4° (22.7 to 33.5°) and the median RI was 37.8° (34.9 to 41.9°). In the generated CT group, the median AA was 25.9° (23.3 to 28.7°), and the median RI was 40.7° (37.8 to 43°). After AA was converted to RA using the

trigonometric function, the median true RA was 18.0° (13.7 to 22.0°), and the median-generated RA was 17.6° (15.1 to 19.3°).

The median RA absolute difference was 3.45° (1.65 to 8.0°), and the median RI absolute difference was 3.25° (1.0 to 7.48°) (Figures 6A and B).

Figure 6C shows each patient's true RA and the absolute difference between the true RA and the generated RA. Figure 6D is about RI. Both graphs suggest that the error tends to be larger when the true CT angle deviates from the median.

Figure 6E shows that the differences between true RA and the median RA were larger in the group where the absolute differences between true RA and generated RA are 10° or more than in the group where the absolute differences are less than 10° (median (IQR); 3.7° (1.9 to 5.8°) in the <10° group versus 12.5° (10.3 to 14.0°) in the ≥10° group, $P < .01$). A similar trend was found for RI in Figure 6F (median (IQR); 3.0° (1.1 to 5.9°) in the <10° group versus 7.0° (5.7 to 10.1°) in the ≥10° group, $P < .01$).

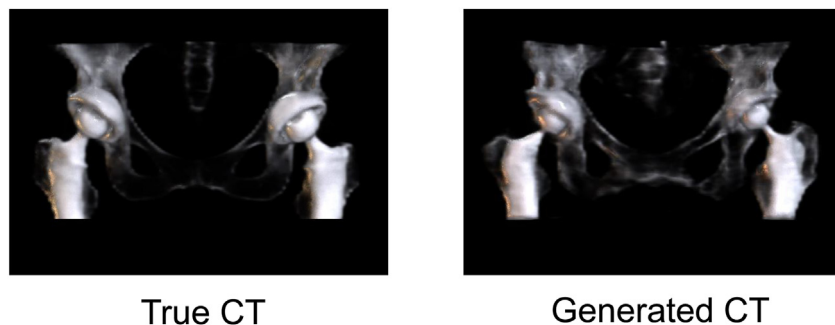


Fig. 5. The results of 3D reconstruction of the X-ray displayed in Figure 3. 3D, 3-dimensional.

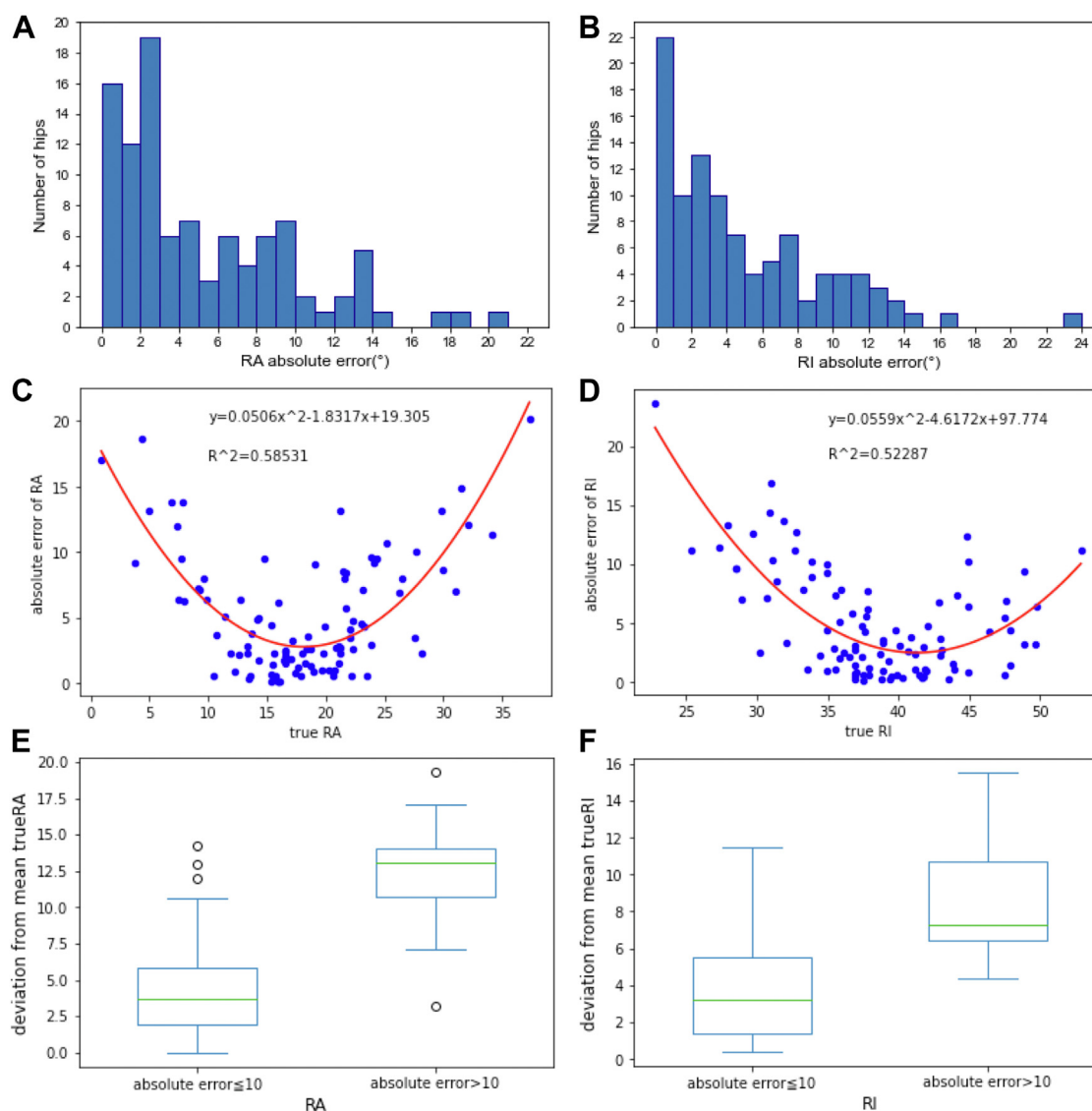


Fig. 6. Left is about RA. Right is about RI. Histograms with the distribution of hip numbers in terms of angle absolute error between on true CT and on generated CT (A and B). The relationship between angle measured on true CT and angle absolute error (C and D). Box-plot comparing the deviation from median angle measured on true CT for angle absolute error $\leq 10^\circ$ group and $> 10^\circ$ group (E, F). RA, radiographic anteversion; RI, radiographic inclination; CT, computed tomography.

Discussion

In this study, we successfully generated 3D reconstruction from single AP postoperative THA X-ray images using GAN. Furthermore, the error between the angle measured on the true CT and the generated CT was approximately 3° , which shows promise for future practical use in clinical practice.

The 2D–3D reconstruction method has been studied in the orthopaedic field for decades. Numerous methods utilizing a 3D statistical shape model to reconstruct 3D shapes from 2D X-ray images have been reported [8,28]. This approach estimates the optimal 3D shape by creating a 3D model from the population mean and deviation and superimposing it on the X-ray image [29]. However, most of these methods have inherent limitations, such as high computational costs and complex operations [16,30]. On the other hand, deep learning–based 3D reconstruction from X-ray images has been studied in the recent years [7,16]. These methods generally do not require complex operations and can perform 3D reconstruction more quickly than statistical shape model–based

methods once the deep learning models have been trained [30]. This deep learning technique has only been applied to reconstruct 3D bone shapes in the hand and spinal regions [7,16]. However, there have been no reports on deep learning–based 3D reconstruction in the hip region. To the best of our knowledge, this study is the first report of 2D–3D reconstruction of not only the pelvic bone but also the implant simultaneously using deep learning techniques. In addition, some reports showed only a part of the 3D reconstruction from DRR images, and not from X-ray images, because of the lack of sufficiently paired original CT and X-ray images [7,21,31]. In this study, we performed 3D reconstruction from X-ray images and suggested the possibility of its actual clinical use in a more concrete manner.

Although we hypothesized that this method would achieve an error of less than 3° from the angle measured on the actual CT, the angle measurement errors of anteversion and inclination were 3.45° and 3.25° , respectively, which were slightly higher than the expected 3° . This is because of large absolute errors in many cases. In fact, of the 100 hips, the number of cases with an absolute error of

10° or more was 14 for RA and 16 for RI. The results showed that the absolute error tended to be larger in cases with improper acetabular cup orientation (Figures 6C and D). Because the number of cases with malpositioning of the acetabular cup was smaller than the number of cases with optimal acetabular cup orientation, the current deep learning model could not be sufficiently trained, resulting in large angle errors. This error problem can be solved by increasing the number of cases with cup malposition and including them in the training dataset of this model, potentially leading to lower measurement errors. In practice, it is difficult to increase the number of such cases because hip surgeons always try to achieve optimal implant positioning, although the use of generative AI might be a solution to this problem by generating such cases.

This study has a few potential limitations. The acetabular component used in this cohort was limited to one product (AHFIX Q3; KYOCERA Corporation, Kyoto, Japan). Therefore, this methodology cannot be easily applied in cases involving other types of acetabular components. In addition, this model does not apply to abnormal cases such as dislocations and retroversion cups. We excluded cases with information on complications from our dataset because we envisioned the model's primary use in normal cases. Additionally, normalizing the dataset is crucial to enhancing the model's accuracy, which necessitated the exclusion of these patients as well. However, this limitation can be resolved if the model is trained using lateral X-ray images. Also, the area of 3D CT reconstruction from the X-ray images was limited to between 10 cm proximal and 5 cm distal to the pubic bone. As the scan range of CT imaging was not clearly defined at our institute, it varied among patients. In these cases, few CT images included the anterior superior iliac spine (ASIS) as the range. Therefore, we could not include ASIS as an image range during normalization of the training data. In the future, sufficient CT data up to the ASIS should be obtained so that angle measurements can be performed based on the anterior pelvic plane, consisting of the bilateral ASIS and pubic tubercles. Additionally, the cohort in the training dataset consists of general patients undergoing THA at our institute, and the analysis of this study did not include their lumbar lordosis and pelvic tilt. Cup placement for a pelvis with major posterior tilt is currently one of the major concerns because it is more prone to dislocation. We will need to examine the accuracy and precision of this 3D reconstruction method for a dataset containing many patients with major posterior pelvic tilt. Furthermore, considering clinical applications, we attempted 3D reconstruction of the X-rays taken in an operating room, although it could not be generated with sufficient accuracy (Supplementary Figure 1). The reason may be that X-ray images taken in the operating room have different image quality compared to regular images because the former are taken with portable X-ray equipment. Moreover, further investigation is needed in multicenter studies to improve the performance of the model for its application in clinical practice.

A completed version of the Checklist for Artificial Intelligence in Medical Imaging [32] is provided (Supplementary Material 2).

In conclusion, we successfully used GANs for the 3D reconstruction of single AP THA postoperative X-ray images. These results show promise for future clinical applications. Further investigation is necessary to enhance the performance of this model.

CRediT authorship contribution statement

Akira Fujita: Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation. **Koji Goto:** Writing – review & editing, Supervision, Resources, Investigation, Conceptualization. **Akihiko Ueda:** Writing – review & editing, Supervision, Methodology, Investigation, Data curation. **Yutaka**

Kuroda: Writing – review & editing, Supervision, Resources, Methodology. **Toshiyuki Kawai:** Writing – review & editing, Supervision, Resources, Methodology. **Yaichiro Okuzu:** Writing – review & editing, Supervision, Resources. **Yasushi Okuno:** Writing – review & editing, Visualization, Supervision, Methodology, Funding acquisition. **Shuichi Matsuda:** Supervision, Resources.

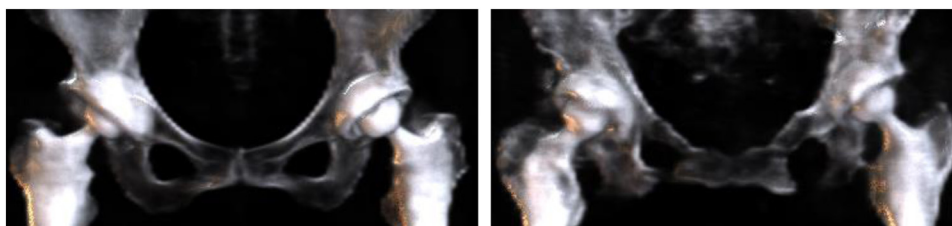
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Appendix**True CT****Generated CT**

Supplementary Figure 1. Results of 3D reconstruction of a radiograph taken in an operating room. 3D, three dimensional; CT, computed tomography.