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Deep Learning-Based Augmented Contrast-Enhancement and Denoising for Reduced-Iodine and Low-Radiation 70-kVp Cerebral CT Angiography: A Prospective Study

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Objective: To evaluate the feasibility of cerebral computed tomography angiography (CTA) obtained with reduced iodine and low radiation at 70 kVp and the effect of deep learning-based augmented contrast enhancement (DL-ACE) and denoising (DL-DN) algorithms on the CTA quality.

Materials and Methods: In this prospective study, 47 healthy volunteers (male:female, 31:16; mean age ± standard deviation, 57.8 ± 10.9 years) were randomly assigned to one of three CTA protocols: Group A (n = 16; 100 kVp, 40 mL of 350 mgI/mL), Group B (n = 16; 70 kVp, 40 mL of 270 mgI/mL), and Group C (n = 15; 70 kVp, 28 mL of 270 mgI/mL [ultralow iodine]), with an injection rate of 2.5 mL/s for all. Images were reconstructed using filtered back projection (FBP), and images in Groups B and C were additionally reconstructed using DL-ACE and DL-DN. Arterial attenuation, image noise, contrast-to-noise ratio (CNR), and subjective image quality were compared among five image sets.

Results: Compared with Group A, Groups B and C received 23.7% lower radiation doses. With FBP, arterial attenuation was significantly higher in Groups B (435.8 ± 50.2 Hounsfield units [HU]) and C (391.8 ± 52.1 HU) than in Group A (321.1 ± 47.4 HU) ($P < 0.001$), while CNR did not differ significantly (Group A, 19.9 ± 4.7; Group B, 20.3 ± 3.8; and Group C, 18.4 ± 4.6) due to higher image noise in Groups B and C. After applying DL-ACE and DL-DN in Groups B and C, arterial attenuation increased by 45.4% and image noise decreased by 34.5%, resulting in significantly higher arterial attenuation, CNR, and subjective image quality compared with Group A ($P < 0.001$).

Conclusion: Cerebral CTA at 70-kVp using ultralow iodine enhanced arterial attenuation but increased image noise compared with the 100-kVp CTA protocol. DL-ACE and DL-DN significantly increased arterial attenuation and reduced image noise, resulting in higher CNR and better subjective image quality.

Keywords: Cerebral artery; Computed tomography angiography; Contrast media; Radiation; Deep learning

INTRODUCTION

Cerebral computed tomography angiography (CTA) is widely used for the noninvasive evaluation of neurovascular diseases [1]. CTA requires sufficient arterial enhancement to achieve high diagnostic performance, which is directly influenced by the amount of intravascular iodine and X-ray energy level [2]. Therefore, high iodine concentration

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contrast media (HC-CM), rapid injection rates, and large volumes of CM are generally used to maximize arterial attenuation [2,3].

Conversely, many researchers have sought to reduce the intravascular iodine load to minimize the risk of contrast-induced acute kidney injury (CI-AKI). CI-AKI is a major cause of iatrogenic acute renal dysfunction and associated with substantial morbidity and mortality, particularly in high-risk patients with renal impairment, diabetes mellitus, heart failure, advanced age, or hemodynamic instability [4-6]. Some studies have used low tube voltage protocols to improve vascular attenuation without increasing intravascular iodine, and reported mean intracranial arterial attenuation values of 355–695.2 Hounsfield units (HU) in 70–80 kVp cerebral CTA with reduced CM volumes [7-14]. However, low tube voltage inevitably increases image noise and can degrade the image quality because of reduced radiation exposure [7-11].

In recent years, deep learning (DL) techniques have been increasingly applied in medical imaging. In particular, DL-based denoising (DL-DN) algorithms for CT have shown impressive performance in reducing the radiation dose while maintaining the image quality [15,16]. Additionally, a novel DL technique has been developed to selectively boost the contrast enhancement provided by iodine CM in post-contrast CT images [17,18]. The deep learning-based augmented contrast enhancement (DL-ACE) algorithm can improve vascular attenuation in CTA without increasing intravascular iodine; therefore, it has the potential to reduce the intravascular iodine load.

In continuation of previous cerebral CTA studies that used a low iodine load [7,8], our study aimed to further reduce the iodine load by applying a 70 kVp protocol in combination with the DL-DN and DL-ACE algorithms. This study had two objectives. The first was to investigate the feasibility of a 70-kVp cerebral CTA protocol with reduced iodine load using low-iodine-concentration CM (LC-CM) compared with a 100-kVp protocol using HC-CM. The second aim was to assess the effects of DL-ACE and DL-DN on the quality of CTA obtained with 70 kVp and reduced iodine load.

MATERIALS AND METHODS

A phantom study was conducted to determine the attenuation values and contrast-to-noise ratio (CNR) of HC-CM (Iohexol 350 mgI/mL; Omnipaque; GE Healthcare, Chicago, IL, USA) and LC-CM (Iodixanol 270 mgI/mL; Visipaque; GE Healthcare) at 100 kVp and 70 kVp, respectively. The clinical study was then designed based on the results of the phantom study (Supplementary Fig. 1). The detailed methodology and results of the phantom study are provided in the Supplement (I. Phantom Study section).

Participants

The study protocol was reviewed and approved by the Institutional Review Board of Gangnam Severance Hospital (IRB No. 3-2018-0068), and written informed consent was obtained from all participants. Forty-seven healthy volunteers with normal renal function were enrolled and randomly assigned to one of three CTA protocols: Group A (100 kVp and 40 mL of HC-CM), Group B (70 kVp and 40 mL of LC-CM), or Group C, referred to as ‘ultralow iodine’ in this study (70 kVp and 28 mL of LC-CM). Randomization was performed using a computer-generated sequence created with Microsoft Excel (RAND function), and each participant was allocated to one of the three groups according to this sequence.

Imaging Techniques

All CTA scans were performed using a 128-channel MDCT (SOMATOM Definition AS+; Siemens Healthineers, Forchheim, Germany). For Group A, the imaging parameters were similar to those used in daily practice at our institution: slice acquisition of 128 x 0.6 mm using a z-flying focal spot technique, pitch of 0.45, gantry rotation time of 0.5 seconds, and exposure setting of 100 kVp and 230 effective tube current-time product (eff·mAs) (calculated as tube current x rotation time/pitch). The expected volume CT dose index (CTDIvol) of the protocol used for Group A was 20.1 mGy. The CT scan range extended from the skull vertex to the posterior arch of the C1 vertebra. For the 70 kVp protocols (Groups B and C), the eff·mAs was adjusted to achieve a CTDIvol as close as possible to that of Group A. However, due to the tube current capacity limitation of the scanner, the maximum available eff·mAs was 550, instead of the theoretically required 724. Consequently, the resulting CTDIvol for the 70 kVp protocol was 15.4 mGy.

HC-CM (Iohexol 350 mgI/mL) and LC-CM (Iodixanol, 270 mgI/mL) were warmed to 37°C before administration and injected into the right antecubital vein via a 20-gauge cannula using a dual-head power injector (Dual Shot, Nemoto Kyorindo, Tokyo, Japan). For Groups A and B, 40 mL of HC-CM and LC-CM, respectively, were injected at a rate of 2.5 mL/s for 16 seconds, followed by an injection of 40 mL of saline at 2.5 mL/s. To evaluate the feasibility of reducing the volume of CM for the 70 kVp protocol, the total volume of LC-CM in Group C was reduced by 30% to 28 mL. The percentage reduction was determined based on the results of the phantom study. Therefore, 28 mL of LC-CM was injected at 2.5 mL/s for 11.2 seconds, followed by a 52 mL saline flush at a rate of 2.5 mL/s. An automatic bolus-tracking program (CARE Bolus; Siemens Healthineers) was used to initiate the CT scan after CM injection. The region of interest (ROI) for bolus tracking was placed in the common carotid artery at the level of the hyoid bone. Thresholds of 125 HU, 100 HU, and 50 HU were used to trigger the CTA in Groups A, B, and C, respectively. A delay of three or four seconds was added before CTA scanning.

Axial CTA images were reconstructed using filtered back-projection (FBP) with a slice thickness of 0.6 mm. Additionally, images from Groups B and C were reconstructed using the DL-ACE (ClariACE, ClariPi Inc., Seoul, Korea) and DL-DN (ClariCT.AI, ClariPi Inc.) algorithms. All images were transferred to online image processing software (Aquarius iNtuition, TeraRecon Inc., Durham, NC, USA) for quantitative and qualitative image analyses.

Deep Learning-Based Algorithms

The DL-DN and DL-ACE algorithms, commercially available vendor-agnostic image reconstruction techniques, were developed using a U-net-based convolutional neural network as denoising and contrast-boosting solutions, respectively. The detailed methodology of these algorithms is provided in the Supplement (II. Deep Learning-based Algorithms section).

Quantitative Analysis

The attenuation value of the cerebral artery was evaluated in the internal carotid artery at the T junction using an ROI (2.1–11.5 mm^2) drawn to encompass the entire vessel lumen, excluding the lumen walls, calcifications, and thrombi. Attenuation of the brain parenchyma was assessed in one occipital lobe, avoiding vascular structures, using a 200 mm^2 ROI. Image noise was defined as the standard deviation of the brain parenchymal attenuation value. All measurements were performed by a radiologist with 4 years of experience in interpreting cerebral CTA, who was blinded to the group allocation and reconstruction techniques. CNR of the cerebral artery was calculated as follows: CNR = (mean arterial attenuation value - brain parenchymal attenuation value)/image noise [9].

To quantitatively evaluate the sharpness and visibility of the cerebral arteries in the images from each protocol, we assessed the edge rise distance (ERD) and edge rise slope (ERS) at the vessel boundaries. ERD was defined as the distance between the pixel locations corresponding to 10% and 90% of the maximum pixel intensity, and ERS was defined as the slope of the line connecting these two points on the CT attenuation profile curves. Shorter ERD and steeper ERS indicate greater vessel edge sharpness [19-21]. Short-line segments were drawn perpendicular to the border of the proximal middle cerebral artery and edge-line profiles were extracted from them, averaged, and plotted using cubic-spline interpolation. ERD and ERS measurements were performed by a single observer using image-processing softwares (ImageJ, National Institutes of Health, Bethesda, MD, USA; MATLAB, Mathworks, Natick, MA, USA).

Qualitative Analysis

Qualitative image analysis of the axial, coronal, and sagittal multiplanar reconstructions, maximum intensity projection images, and volume-rendering images of cerebral CTA was performed independently by two radiologists with 7 and 11 years of experience in cerebral CTA interpretation. Arterial enhancement, sharpness of the arterial boundary, and overall diagnostic image quality of each cerebral CTA image were recorded using a five-point scale (1 = bad, nondiagnostic; 2 = poor, substandard; 3 = moderate, standard; 4 = good, better than standard; 5 = excellent). Image noise was graded using a five-point scale (1 = no diagnosis possible; 2 = substantial; 3 = moderate, acceptable; 4 = minor; 5 = no graininess). The CT datasets were randomized and independently scored by both readers who were blinded to the scanning protocols, reconstruction methods for the CT images, and amount of iodine used. For the qualitative comparison between the groups, the scores from the two readers were averaged for each participant. When arterial enhancement and image noise were specifically assessed, the window level and width were fixed at 200 and 800, respectively, to enable a direct comparison between the groups [9].

Dose Calculation

CTDIvol and dose-length product (DLP) provided by the CT scanner after scanning were recorded. The effective dose (ED) was calculated by multiplying the DLP by a conversion factor of 0.0023 mSv/(mGy·cm) [9,22,23].

Statistical Analysis

All statistical analyses were performed using SPSS version 25 (IBM Corp., Armonk, NY, USA). Demographic, morphometric (age, height, and weight), and quantitative measurement data were compared among the groups using independent *t*-tests. Qualitative scores were compared using the Mann–Whitney U test. The data obtained before and after applying the DL algorithms in Groups B and C were compared using paired *t*-tests. For multiple comparisons, Bonferroni corrections were applied appropriately: the statistical significance threshold for *P*-values was 0.025 (0.05/2) for two pairwise comparisons (Group A vs. Group B or Group C) for demographic or morphometric data, and 0.0125 (0.05/4) for four pairwise comparisons among the image sets (Group A with FBP as the reference vs. Groups B and C reconstructed with FBP and DL-ACE/DL-DN). Otherwise, *P*-values less than 0.05 were considered statistically significant. Linear-weighted kappa statistics were used to assess interobserver agreement in scoring and were interpreted according to the guidelines of Landis and Koch [24].

RESULTS

Participants

All 47 participants were randomly assigned to Group A (n = 16), Group B (n = 16), or Group C (n = 15). There were no significant differences in age, height, or weight between Group A and Groups B and C ($P \geq 0.068$ for both) (Table 1).

Quantitative Analysis

The quantitative analysis results for the three groups are shown in Figure 1 and Table 2. When FBP was applied, the arterial attenuation values in Groups B and C were 35.7% and 22.0% higher than those in Group A, despite reductions in the iodine load by 3.2 g (Group B) and 6.4 g (Group C). However, CNR did not differ significantly between Group A and Groups B and C because the image noise in Groups B and C was significantly higher than that in Group A due to a 23.7% lower CTDIvol in Groups B and C (Figs. 2-4).

After applying DL-ACE and DL-DN to Groups B and C, the arterial attenuation values increased by a mean of 45.4% ($P < 0.001$) and the image noise decreased by a mean of 34.5% ($P < 0.001$), resulting in a mean CNR improvement of 128.6% in Groups B and C ($P < 0.001$). Compared with Group A reconstructed with FBP, Groups B and C reconstructed with DL-ACE had 97.7% and 77.0% higher mean arterial attenuation, respectively. After applying DL-DN, the image noise in Groups B and C was not significantly different

Table 1. Characteristics of the 47 participants

Characteristic	Group A (n = 16)	Group B (n = 16)	Group C (n = 15)
Age, yr	57.1 ± 8.1	57.3 ± 12.2	59.2 ± 12.5
Sex, male:female	10:6	11:5	10:5
Height, cm	167.6 ± 6.8	162.9 ± 8.0	162.5 ± 8.0
Weight, kg	72.9 ± 15.7	65.4 ± 10.8	65.6 ± 10.8

Values are means ± standard deviations or numbers

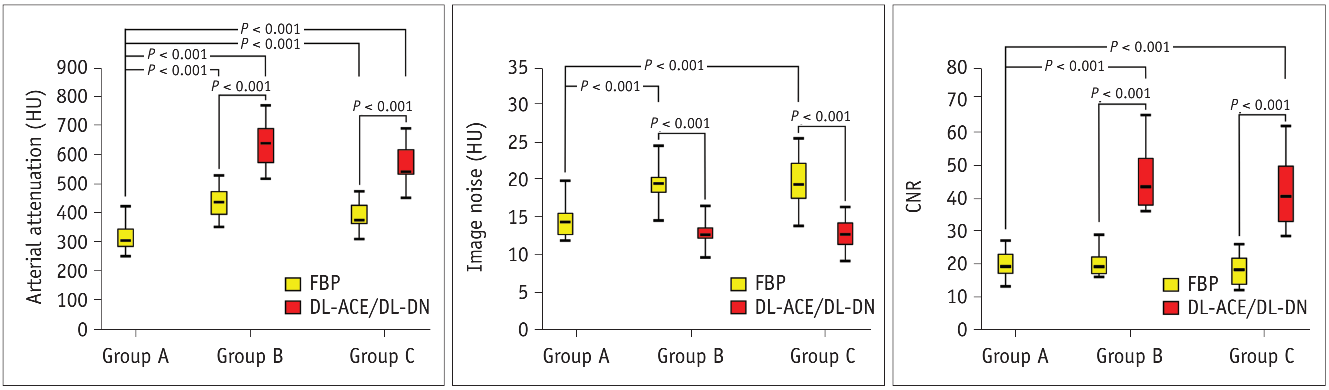

Fig. 1. Box-and-whisker plot of the arterial attenuation value, image noise, and CNR in cerebral CT angiography. *P*-values are provided only for statistically significant comparisons. After FBP reconstruction, Groups B (70 kVp, 10.8 g iodine) and C (70 kVp, 7.6 g iodine) showed significantly higher arterial attenuation than Group A (100 kVp, 14.0 g iodine); however, they did not demonstrate higher CNRs than Group A due to higher image noise. The DL-ACE and DL-DN algorithms significantly increased arterial attenuation and reduced image noise in Groups B and C, resulting in significantly higher CNRs than that in Group A reconstructed with FBP. CNR = contrast-to-noise ratio, FBP = filtered back projection, DL-ACE = deep learning-based augmented contrast enhancement algorithm, DL-DN = deep learning-based denoising algorithm, HU = Hounsfield unit

Table 2. Quantitative image quality assessment

Parameter	FBP					DL-ACE/DL-DN			
	Group A	Group B	*P**	Group C	*P**	Group B	*P**	Group C	*P**
Artery attenuation value, HU	321.1 ± 47.4	435.8 ± 50.2	<0.001†	391.8 ± 52.1	<0.001†	634.8 ± 71.6	<0.001†	568.4 ± 75.0	<0.001†
Image noise, HU	14.6 ± 2.2	19.6 ± 2.6	<0.001†	19.9 ± 3.4	<0.001†	13.0 ± 1.8	0.029	12.9 ± 2.1	0.035
CNR	19.9 ± 4.7	20.3 ± 3.8	0.825	18.4 ± 4.6	0.352	46.1 ± 8.9	<0.001†	42.2 ± 10.8	<0.001†
ERD, mm	1.75 ± 0.46	1.92 ± 0.34	0.233	1.88 ± 0.41	0.419	1.75 ± 0.21	0.982	1.71 ± 0.24	0.786
ERS, HU/mm	141.9 ± 36.4	163.5 ± 37.5	0.109	163.0 ± 43.3	0.151	264.7 ± 46.2	<0.001†	258.2 ± 57.3	<0.001†

Values are means ± standard deviations. Group A = 100 kVp and 40 mL of 350 mgI/mL CM, Group B = 70 kVp and 40 mL of 270 mgI/mL CM, Group C = 70 kVp and 28 mL of 270 mgI/mL CM.

*For comparison with Group A reference, †Statistically significant results after the Bonferroni correction, i.e., *P*-value <0.0125 (0.05/4).

CM = contrast medium, FBP = filtered back projection, DL-ACE = deep learning-based augmented contrast enhancement algorithm, DL-DN = deep learning-based denoising algorithm, HU = Hounsfield unit, CNR = contrast-to-noise ratio, ERD = edge rise distance, ERS = edge rise slope

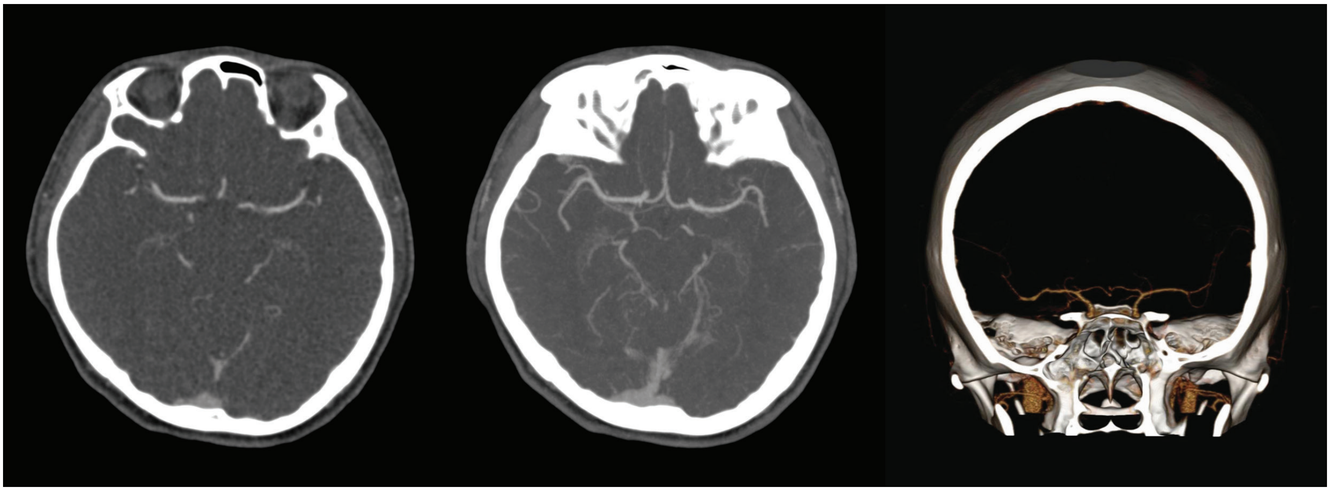

Fig. 2. Cerebral CT angiography using 100 kVp and 40 mL of 350 mgI/mL contrast medium (14 g of iodine) in a 29-year-old female. Axial image with a 0.6 mm slice thickness (right), maximum intensity projection with a slab thickness of 10 mm (middle), and volume rendering technique (left) of CT images reconstructed with filtered back projection. The arterial attenuation value, image noise, and contrast-to-noise ratio were 322.7 HU, 12.4 HU, and 22.2, respectively. HU = Hounsfield unit

from that in Group A with FBP. Consequently, Groups B and C with DL-ACE and DL-DN showed mean CNR increases of 131.3% and 111.8%, respectively, compared with Group A with FBP ($P < 0.001$ for both) (Table 2, Figs. 2-4).

The use of DL-ACE and DL-DN produced sharper vascular boundaries than FBP in the ERD and ERS analyses. When FBP was applied, neither ERD nor ERS differed significantly between Group A and Groups B and C. However, after applying DL-ACE and DL-DN, the ERD of Groups B and C decreased significantly ($P = 0.003$ and $P = 0.009$, respectively) and their ERS increased significantly ($P < 0.001$ for both) compared with the FBP reconstruction. The ERS of Groups B and C reconstructed with DL-ACE and DL-DN were significantly higher than that of Group A reconstructed with FBP ($P < 0.001$ for both), whereas their ERD values were not significantly different from that of Group A (Table 2).

Qualitative Analysis

In the subjective assessment of image quality, the interobserver agreement between the two readers was good, with a linear-weighted kappa value of 0.688. With FBP reconstruction, the subjective scores for arterial enhancement, arterial boundary sharpness, and overall image quality were significantly higher in Group B than in Group A, whereas image noise did not differ significantly between the two groups. In contrast, none of the qualitative scores differed significantly between Group C and Group A. After applying DL-ACE and DL-DN to Groups B and C, all their subjective scores increased significantly compared with their FBP reconstructions ($P \leq 0.001$ for all), and all scores for Groups B and C reconstructed with DL-ACE and DL-DN were significantly higher than those for Group A reconstructed with FBP ($P < 0.001$ for all) (Table 3).

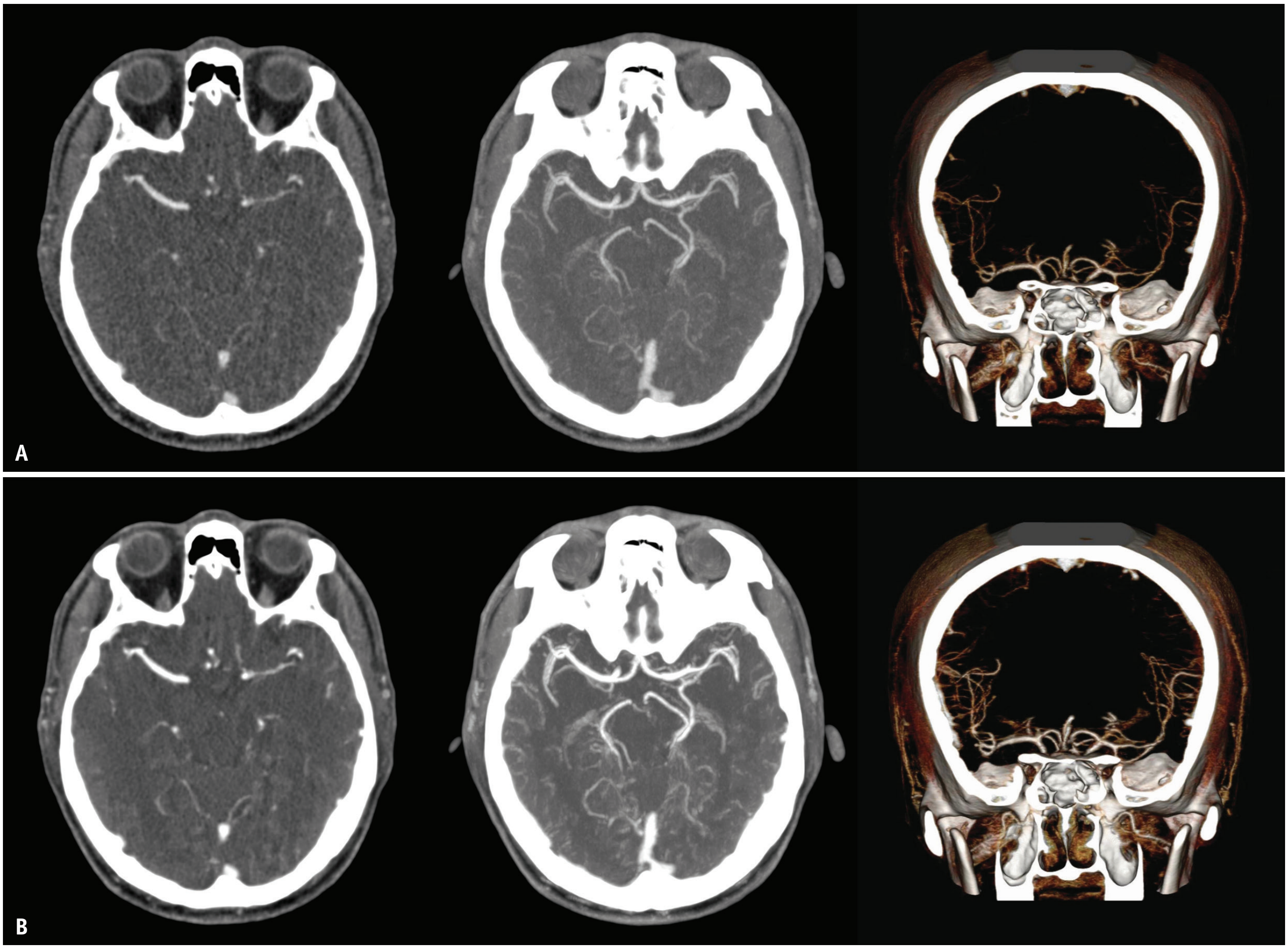

Fig. 3. Cerebral CT angiography using 70 kVp and 40 mL of 270 mgI/mL contrast medium (10.8 g of iodine) in a 43-year-old male. **A, B:** Axial image, maximum intensity projection, and volume rendering technique of CT images reconstructed using FBP **(A)** and deep learning-based algorithms **(B)**. The deep learning-based augmented contrast enhancement and denoising algorithms significantly increased arterial attenuation (from 478.8 to 699.4 HU) and reduced image noise (from 19.2 to 13.2 HU), resulting in an improved contrast-to-noise ratio (from 21.9 to 48.2) compared with images reconstructed with FBP. FBP = filtered back projection, HU = Hounsfield unit

Radiation Dose

The CTDIvol, DLP, and estimated ED in Group B (15.25 ± 0.01 mGy, 260.4 ± 35.5 mGy·cm, and 0.60 ± 0.08 mSv, respectively) and Group C (15.26 ± 0.01 mGy, 273.1 ± 50.3 mGy·cm, and 0.63 ± 0.12 mSv, respectively) were 23.7%, 22.3%, and 22.8% lower, respectively, than those in Group A (19.99 ± 0.05 mGy, 345.5 ± 22.4 mGy·cm, and 0.79 ± 0.05 mSv; $P < 0.001$ for all).

DISCUSSION

This study demonstrated the feasibility of a 70 kVp cerebral CTA protocol using an ultralow iodine load and low radiation, and assessed the effectiveness of the DL-ACE and DL-DN algorithms with this protocol. Compared with 100 kVp cerebral CTA using 14.0 g iodine (Group A), 70 kVp cerebral CTA using 7.6 g iodine (Group C) provided higher arterial attenuation but did not improve CNR due to increased image noise from the lower radiation dose. The application of DL-ACE and DL-DN to 70 kVp cerebral CTA further increased arterial attenuation and decreased image noise, resulting in higher CNR and superior image quality compared with the 100 kVp protocol.

Previous studies have applied low-tube-voltage protocols to reduce the required amount of CM or iodine load. In studies using 70 or 80 kVp protocols for cerebral CTA, the mean attenuation of the intracranial arteries ranged from 355 HU to 695.2 HU [7-9,12-14]. In particular, a study using a 70 kVp protocol with 64 mL of 370 mgI/mL CM (23.7 g iodine) reported the highest mean attenuation of 695.2 HU for the intracranial arteries [7]. In our study, the

70 kVp protocol yielded mean arterial attenuation values of 435.8 HU with the administration of 40 mL (10.8 g iodine) and 391.8 HU with 28 mL (7.6 g iodine) of 270 mgI/mL CM.

Low tube voltage protocols also reduce the radiation dose. However, they inevitably increase image noise, which can degrade the image quality. In our study, CTDIvol of the

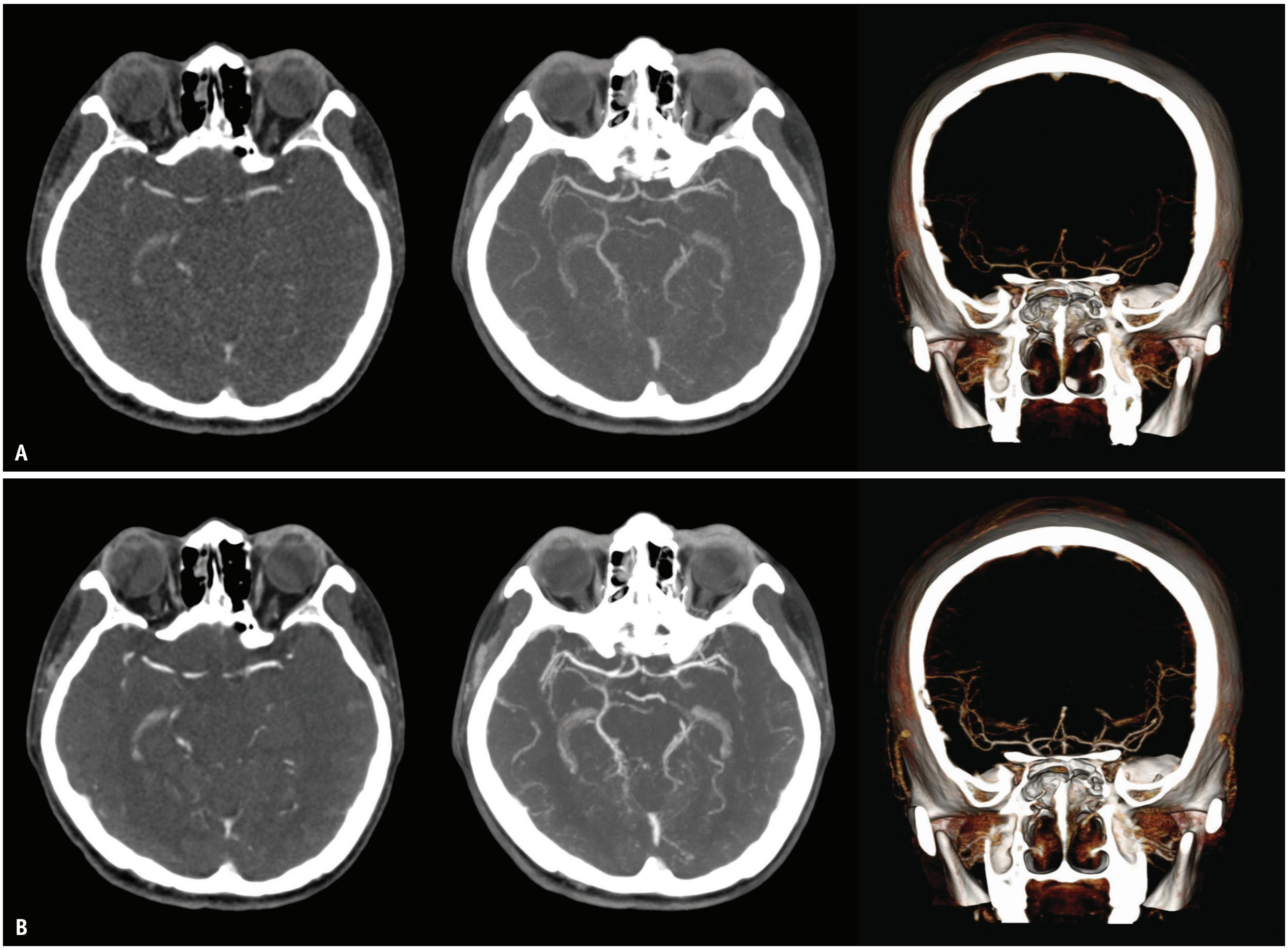

Fig. 4. Cerebral CT angiography using 70 kVp and 28 mL of 270 mgI/mL contrast medium (7.6 g of iodine) in a 53-year-old female. **A, B:** Axial image, maximum intensity projection, and volume rendering technique of CT images reconstructed using FBP **(A)** and deep learning-based algorithms **(B)**. The deep learning-based augmented contrast enhancement and denoising algorithms significantly increased arterial attenuation (from 366.3 to 538.3 HU) and reduced image noise (from 17.6 to 11.7 HU), resulting in an improved contrast-to-noise ratio (from 18.3 to 41.9) compared with images reconstructed using FBP. FBP = filtered back projection, HU = Hounsfield unit

Table 3. Qualitative subjective image quality assessment

Parameter	FBP					DL-ACE/DL-DN			
	Group A	Group B	*P**	Group C	*P**	Group B	*P**	Group C	*P**
Arterial enhancement	2.5 (2.0, 3.0)	3.0 (3.0, 3.6)	0.004†	3.5 (3.0, 3.8)	0.030	5.0 (4.0, 5.0)	<0.001†	5.0 (4.5, 5.0)	<0.001†
Image noise	2.5 (2.5, 3.0)	2.5 (2.0, 2.5)	0.080	2.5 (2.0, 3.0)	0.379	4.5 (4.4, 5.0)	<0.001†	4.5 (4.0, 5.0)	<0.001†
Arterial boundary sharpness	2.3 (2.0, 2.8)	3.5 (3.0, 3.5)	0.005†	3.0 (2.8, 3.8)	0.041	5.0 (4.5, 5.0)	<0.001†	5.0 (4.5, 5.0)	<0.001†
Overall image quality	2.5 (2.0, 2.8)	3.0 (3.0, 3.5)	0.010†	3.0 (2.5, 3.5)	0.086	5.0 (4.5, 5.0)	<0.001†	4.5 (4.5, 5.0)	<0.001†

Values are the medians (first and third quartiles) of the qualitative scores averaged across the two readers for each participant. Group A = 100 kVp and 40 mL of 350 mgI/mL CM, Group B = 70 kVp and 40 mL of 270 mgI/mL CM, Group C = 70 kVp and 28 mL of 270 mgI/mL CM. *For comparison with Group A reference, †Statistically significant results after the Bonferroni correction, i.e., *P*-value <0.0125 (0.05/4). CM = contrast medium, FBP = filtered back projection, DL-ACE = deep learning-based augmented contrast enhancement algorithm, DL-DN = deep learning-based denoising algorithm

70 kVp protocol was 23.7% lower than that of the 100 kVp protocol due to the scanner's tube current capacity limitation. Consequently, image noise was 25.9% higher, and CNR was not significantly improved compared with the 100 kVp protocol, despite the higher arterial attenuation.

Recently, DL-based algorithms have received significant attention for their potential to reduce image noise and improve spatial and contrast resolution, thereby allowing reductions in both the radiation dose and iodine load while maintaining the image quality and contrast [17,18,25]. In our study, the DL-ACE and DL-DN algorithms increased arterial attenuation and reduced image noise, leading to significant improvements in CNR, arterial boundary sharpness, and subjective image quality.

In a previous study, the DL-DN algorithm demonstrated significant image noise reduction in low-dose liver CT (66.7% lower radiation dose) and provided non-inferior overall image quality compared with standard-dose CT using model-based iterative reconstruction [25]. The DL-ACE algorithm was designed to augment the iodine attenuation with the aim of reducing the iodine load. The application of DL-ACE and DL-DN to dual low-dose liver CT, with 19.8% less radiation and 27% less iodine, improved CNR and portal vein conspicuity without compromising the detection of focal hepatic lesions [18].

This study has several limitations. The sample size was relatively small and the study was conducted in healthy volunteers. Large-scale investigations involving patients with diverse neurovascular diseases, such as atherosclerotic stenosis, calcified plaques, or small aneurysms, are necessary to validate the performance of the 70 kVp CTA protocol with DL-based algorithms for detecting these lesions. Future research should also include clinical outcomes, such as diagnostic accuracy for neurovascular diseases and patient safety with respect to CI-AKI and radiation exposure, to establish the clinical relevance of this cerebral CTA protocol and the DL-ACE and DL-DN algorithms.

In conclusion, 70 kVp cerebral CTA with an ultralow iodine load achieved higher arterial attenuation compared with the 100-kVp CTA protocol. However, it did not demonstrate superior CNR due to the increased image noise from the low radiation dose. The application of the DL-ACE and DL-DN algorithms further improved arterial attenuation and reduced image noise, resulting in more than doubling of CNR and improved subjective image quality.

Supplement

The Supplement is available with this article at https://doi.org/10.3348/kjr.2025.1520.

Availability of Data and Material

The datasets generated or analyzed during the study are available from the corresponding author on reasonable request.

Conflicts of Interest

E.S. Cho, the corresponding author and a shareholder of ClariPi, Inc., had no access to or control over the raw data and did not participate in data collection or statistical analysis. J.H. Kim is a shareholder of ClariPi, Inc., and C. Ahn is an employee of ClariPi Inc.; they developed the deep learning algorithms and participated in image-reconstruction processing, but had no access to the study data and no involvement in statistical analysis.
The other authors have no potential conflicts of interest to disclose.

Author Contributions

Conceptualization: Eun-Suk Cho. Data curation: Seunghyun Song, YuSik Kim. Formal analysis: Seunghyun Song, YuSik Kim. Funding acquisition: Eun-Suk Cho. Investigation: Seunghyun Song, Eun-Suk Cho, YuSik Kim. Methodology: Seunghyun Song, Sang Hyun Suh. Project administration: Eun-Suk Cho. Resources: Eun-Suk Cho. Software: Chulkyun Ahn, Jong Hyo Kim. Supervision: Eun-Suk Cho, Sang Hyun Suh, Jae-Joon Chung. Validation: Sang Hyun Suh, Jae-Joon Chung. Visualization: Seunghyun Song. Writing—original draft: Seunghyun Song, Eun-Suk Cho. Writing—review & editing: all authors.

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