Imaging Science in Dentistry 2022; 52: 393-8
https://doi.org/10.5624/isd.20220125

Synthesis of T2-weighted images from proton density images using a generative adversarial network in a temporomandibular joint magnetic resonance imaging protocol

Chena Lee[1], Eun-Gyu Ha[1], Yoon Joo Choi[1], Kug Jin Jeon[1], Sang-Sun Han[1,*]

[1]*Department of Oral and Maxillofacial Radiology, Yonsei University College of Dentistry, Seoul, Korea*

ABSTRACT

Purpose: This study proposed a generative adversarial network (GAN) model for T2-weighted image (WI) synthesis from proton density (PD)-WI in a temporomandibular joint (TMJ) magnetic resonance imaging (MRI) protocol.

Materials and Methods: From January to November 2019, MRI scans for TMJ were reviewed and 308 imaging sets were collected. For training, 277 pairs of PD- and T2-WI sagittal TMJ images were used. Transfer learning of the pix2pix GAN model was utilized to generate T2-WI from PD-WI. Model performance was evaluated with the structural similarity index map (SSIM) and peak signal-to-noise ratio (PSNR) indices for 31 predicted T2-WI (pT2). The disc position was clinically diagnosed as anterior disc displacement with or without reduction, and joint effusion as present or absent. The true T2-WI-based diagnosis was regarded as the gold standard, to which pT2-based diagnoses were compared using Cohen's κ coefficient.

Results: The mean SSIM and PSNR values were 0.4781(±0.0522) and 21.30(±1.51) dB, respectively. The pT2 protocol showed almost perfect agreement (κ=0.81) with the gold standard for disc position. The number of discordant cases was higher for normal disc position (17%) than for anterior displacement with reduction (2%) or without reduction (10%). The effusion diagnosis also showed almost perfect agreement (κ=0.88), with higher concordance for the presence (85%) than for the absence (77%) of effusion.

Conclusion: The application of pT2 images for a TMJ MRI protocol useful for diagnosis, although the image quality of pT2 was not fully satisfactory. Further research is expected to enhance pT2 quality. ***(Imaging Sci Dent 2022; 52: 393-8)***

KEY WORDS: Deep Learning; Computer Neural Network; Artificial Intelligence; Temporomandibular Joint Disorders; Magnetic Resonance Imaging

Introduction

Magnetic resonance imaging (MRI) is an essential tool for the diagnosis of temporomandibular joint disease.[1] Through MRI, the articular disc, joint effusion, and muscle-attached ligaments can be evaluated.[1] Morphological features and the relative location of these anatomic structures are assessed in closed- and open-mouth positions.[1] For patients who experience pain when opening the mouth, it is difficult to obtain open-position images with adequate quality due to movement artifacts.

Multiple sequence types of MRI are required for joint evaluation. Navallas et al.[2] suggested protocols composed of proton density (PD)- and fat-suppressed T2-weighted imaging (WI) in the sagittal view and T1-WI in the coronal view in the review study. PD-WI is generally used as a sequence for disc and ligament evaluation in joints throughout the body.[3] T2-WI, as a fluid-sensitive sequence, best depicts joint effusion as areas of hyperintensity.[1,2]

Although the time required for MRI acquisition has dramatically decreased due to technical advances, such as compressed sensing, the application of rapid imaging technology in clinics has not yet been widely implemented due to limitations including a long reconstruction time.[4,5] Cur-

This work was funded by a National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIT) (No. 2022R1A2B5B01002517).
Received July 14, 2022; Revised September 2, 2022; Accepted September 24, 2022
Published online October 12, 2022
*Correspondence to : Prof. Sang-Sun Han
Department of Oral and Maxillofacial Radiology, Yonsei University College of Dentistry, 50-1 Yonsei-ro Seodaemun-gu, Seoul 03722, Korea
Tel) 82-2-2228-8843, E-mail) sshan@yuhs.ac

Imaging Science in Dentistry · pISSN 2233-7822 eISSN 2233-7830

rently, it takes 2-3 minutes to obtain one sequential series in the temporomandibular joint (TMJ) protocol. For patients who have difficulties maintaining a mouth-open posture, sufficient images may not be obtained for an accurate diagnosis.

Meanwhile, convolutional neural network (CNN) deep learning research has rapidly emerged as a technique in this field. The generative adversarial network (GAN) is a newly introduced system consisting of a generator CNN and discriminator CNN for image-to-image translation. The generator CNN is trained to generate fake images, while the discriminator CNN is trained to discriminate fake images from the ground truth. Then, discriminator error is back-propagated to the generator to help synthesize images closer to the ground truth.[6] For medical imaging, this method is being actively studied for noise reduction and resolution enhancement in MRI and computed tomography.[7,8] However, few studies have explored ways of generating different tissue contrast images based on other pulse sequence images.

Therefore, in this study, the pix2pix GAN was utilized to generate TMJ T2-WI sequences based on PD-WI. Pix2pix is an algorithm that is widely used for image synthesis in the medical field and is known to show generally good performance.[9] Thus, this study aimed to propose a method for the synthesis of T2-WI and to validate its usefulness in a TMJ MRI protocol.

Materials and Methods

The overall workflow of the study is described in Figure 1.

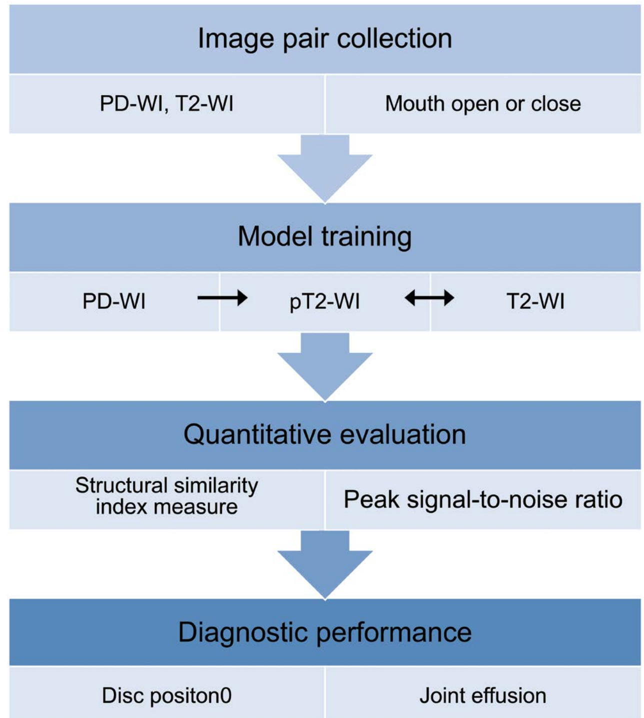

Fig. 1. Workflow of the overall study. SSIM: structural similarity index measure, PSNR: peak signal-to-noise ratio.

Subject

A total of 314 patients who underwent TMJ MRI examinations due to a clinical diagnosis of TMJ disease, at Yonsei University Dental Hospital between January and May 2019 were included. Six patients with poor image quality due to metal artifacts with orthodontic brackets were excluded. Among 308 patients, 90% (n = 277) were used for the training and validation sets, while 10% (n = 31) were used for the test set. For the training data set, bilateral PD and T2 sagittal image pairs in the mouth-closed position (166 patients, 3417 images) and the mouth-open position (111 patients, 2293 images) were included. This study was approved by the institutional review board (IRB) of the authors' institution, and due to its retrospective nature, the requirement for informed consent of patients was exempted (no. 2-2020-0014). All MRI data were extracted with a complete anonymization process.

MRI scan protocol and imaging data

The MRI scans were acquired with a 3.0-T scanner (Signa Pioneer, GE Healthcare, Chicago, IL, USA) with a medium flex-coil. The PD sagittal sequence parameters were as follows: matrix, 280 × 240; field of view, 120 × 120 mm; slice thickness, 2.5 mm; image number, 20-22 slides; repetition time, 2000 ms; echo time, 45.44 ms; number of excitations, 2; sequence duration, ~3 min. The T2 sagittal sequence parameters were as follows: matrix, 280 × 220; field of view, 120 × 120 mm; slice thickness, 2.5 mm; image number, 20-22 slides; repetition time, 3200 ms; echo time, 76.05 ms; number of excitations, 2; sequence duration, ~3 min 30 s. The parameters for the mouth-open and mouth-closed positions were the same.

All image slides were extracted in the JPEG format from the picture archive and communication system (Zetta PACS, Tae-young soft, Anyang, Korea) and resized into 512 × 512 pixels. The 7004 images consisting of PD and T2 pairs were divided into a training set (5710 images) and a test set (1294 images).

Training strategy

The deep learning model used in this study was based on the pix2pix GAN algorithm (Fig. 2). This model is known as a general-purpose network for image-to-image

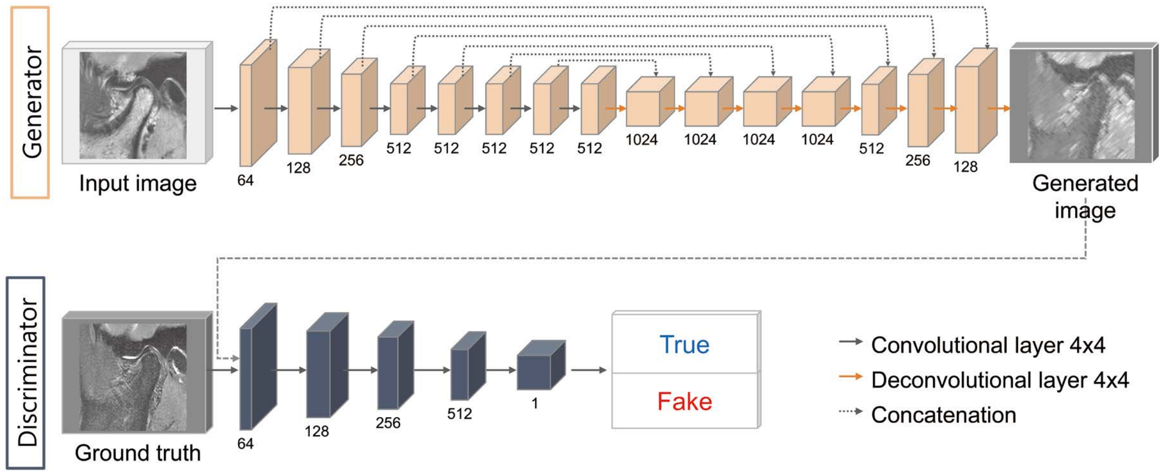

Fig. 2. Structure of the pix2pix generative adversarial network model used in the current study. The overall model is composed of two parts: a generator and a discriminator. The generator produces a fake T2-weighted image (WI) when a reference proton density-WI is input. Then, the discriminator compares the generated T2-WI with the true T2-WI to determine whether it is true or fake. When the generated T2-WI is determined to be fake, the model starts to synthesize an image again.

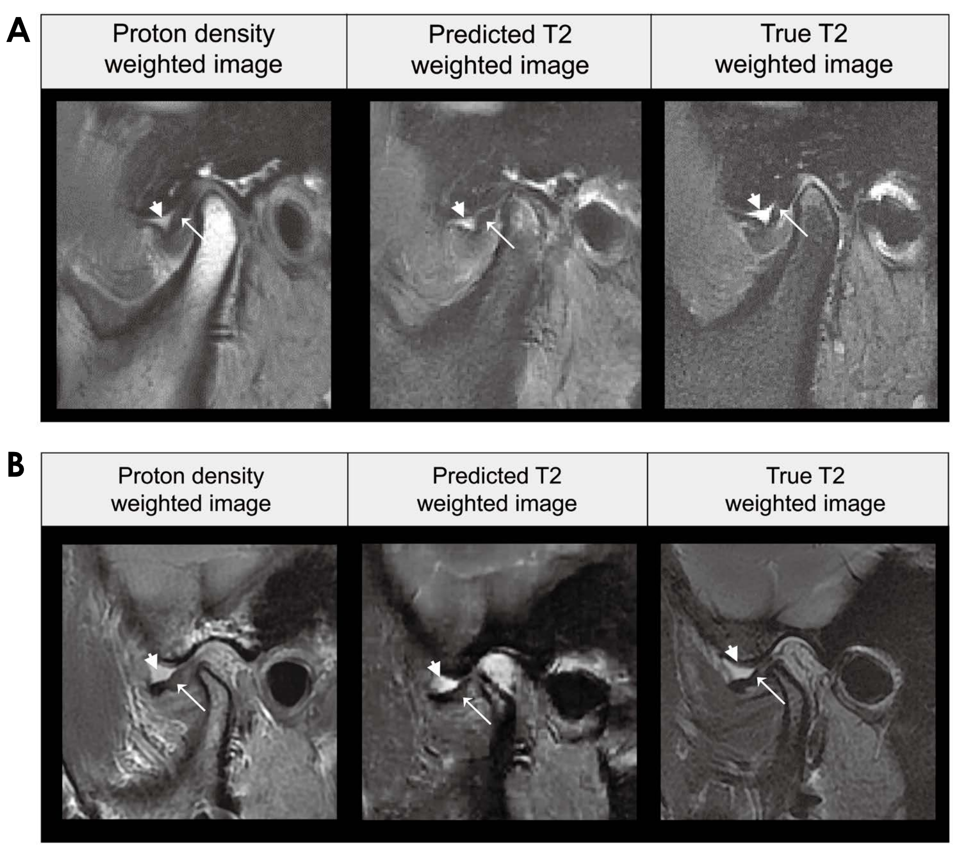

Fig. 3. Anterior disc displacement and effusion can be diagnosed in proton density-weighted image (WI), T2-WI, and predicted T2-WI (arrow, disc; arrowhead, effusion). Closed-mouth position (A) and open-mouth position (B).

translation and consists of an image generator and discriminator. In the generator based on a U-Net composed of convolutional and deconvolutional layers, a fake image is generated from a source image. The discriminator then compares this fake image with the ground truth image to predict whether it is a true image or a fake image in the last layer. The generator is trained to generate a fake image that is indistinguishable from the ground truth image, and the discriminator is trained to better detect fake images, so that the generated image can be optimized in detail or re-gen-

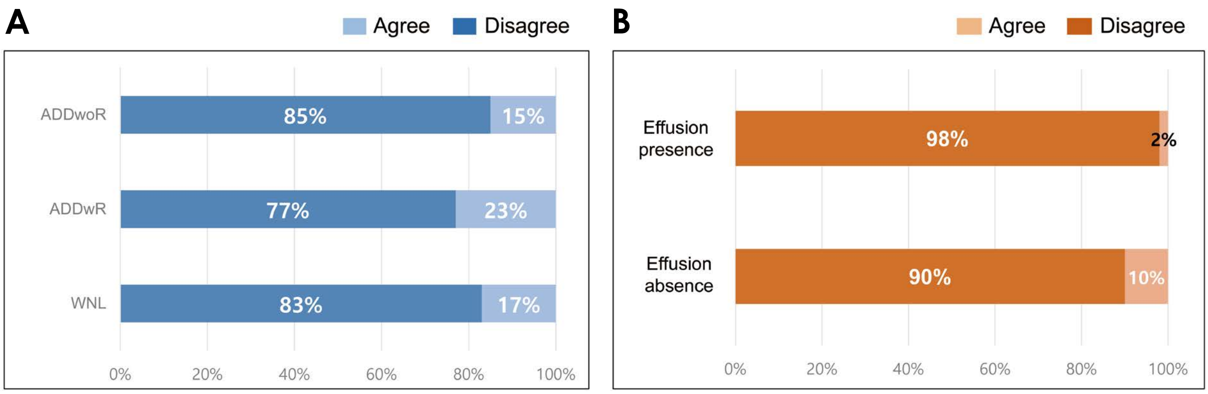

Fig. 4. Diagnostic agreement of the temporomandibular joint protocol with the predicted T2-weighted images in terms of disc displacement (A) and joint effusion (B). ADDwoR: anterior disc displacement without reduction, ADDwR: anterior disc displacement with reduction, WNL: within normal limits.

erated in the generator.[10,11] The training and validation procedures of the model were performed 100 times with the training set of PD and T2 pairs to determine the optimal parameters. The test data were input into the trained model and predicted images were obtained.

Quantitative assessment of model performance

The predicted T2 (pT2) images were evaluated with reference to the true T2 image using the structural similarity index measure (SSIM) and peak signal-to-noise ratio (PSNR). pT2 image sets from both joint sides in the mouth-open and mouth-closed positions were evaluated. The SSIM evaluates the similarity of two images in the aspects of brightness, contrast, and structure. The generated image is more similar to the reference when the SSIM value is closer to 1.[12] The PSNR is an index for evaluating the quality loss of the generated image. Typical values for the PSNR in generated images are between 30 and 50 dB, where higher is better.[13] Previous studies on the head and neck region showed SSIM values between 0.70 and 0.89 and PSNRs between 25 and 30 dB.[14]

$$SSIM = \frac{(2\mu_{\hat{y}_i}\mu_{y_{i,k}} + c_1)(2\sigma_{\hat{y}_i y_{i,k}} + c_2)}{(\mu^2_{\hat{y}_i} + \mu^2_{y_{i,k}} + c_1)(\sigma^2_{\hat{y}_i} + \sigma^2_{y_{i,k}} + c_2)} \tag{1}$$

$$PSNR = 10 \times \log\left(\frac{f^2_{max}}{rmse^2}\right) \tag{1}$$

Clinical image evaluation

Thirty-one sets (62 joints) of the MRI protocol with pT2 or the true T2-WI images were evaluated in terms of disc displacement and joint effusion. The imaging diagnosis of disc displacement and joint effusion followed the diagnostic criteria of a previous study.[15] If the joint with the disc was positioned within the normal range during mouth opening and closing, it was defined as within normal limits (WNL). A disc displaced when the mouth was closed with reduction to the normal position when the mouth was open was defined as anterior disc displacement with reduction (ADDwR). If the disc maintained a displaced position during mouth opening, it was defined as anterior disc displacement without reduction (ADDwoR). Joint effusion was determined as either present or absent.

The diagnoses based on the protocol with pT2 images were then compared with that of the true T2 images. The kappa (κ) coefficient was obtained with a 95% confidence interval. All image evaluation procedures were conducted by two oral and maxillofacial radiologists. The inter-evaluator correlation coefficient (ICC) was obtained with a 95% confidence interval.

Results

The mean SSIM value was 0.4781 ± 0.0522 (minimum, 0.2461; maximum, 0.5403) and the PSNR was 21.30 ± 1.51 dB (minimum, 15.62; maximum, 23.56). When the pT2-WI protocol was evaluated, the κ coefficient was 0.81 (almost perfect agreement) for disc displacement and 0.88 (almost perfect agreement) for effusion (Fig. 3). In terms of disc position, ADDwoR cases showed more consistent results in comparison with the gold standard, and ADDwR cases showed fewer correct diagnoses (Fig. 4A). Furthermore, cases with effusion showed more correct diagnoses than cases with no effusion (Fig. 4B). The ICC between the 2 evaluators was 0.959.

Discussion

The current study was conducted for the purpose of saving acquisition time in the TMJ MRI protocol. For the first time, to the best of the authors' knowledge, this study tried to synthesize T2-WI based on PD-WI using a GAN in the TMJ protocol. The generated images were evaluated using both quantitative metrics and the perspective of radiologists. Although the quantitative indices did not present satisfactory values, the clinical diagnosis based on TMJ MRI protocol with synthetic T2 images closely agreed with the ground truth. This would be particularly helpful for patients who have difficulty maintaining the mouth-open position for a long time during MRI acquisition.

Efforts to reduce the acquisition time through multi-modality synthesis of MRI are of great interest. The introduction of the multidynamic multiecho (MDME) sequence, which synthesizes 6 different sequences including T1-, T2-, and PD-WI from a single acquisition, and was evaluated in the MAGiC trial, was expected to solve these time barriers of MRI.[16,17] Its clinical application remains limited due to its long acquisition time, low resolution, and high susceptibility to artifacts.[17-19] With the development of deep-learning GAN, researchers have recently studied cross-modality syntheses through this technique.[20,21]

A previous study tried to synthesize fluid-attenuated inversion recovery (FLAIR) sequences in brain MRI of patients with acute ischemic stroke.[20] They tried to generate FLAIR images from diffusion-weighted images and evaluated the feasibility of replacing the true image with a synthetic one. The agreement between the true and generated FLAIR was comparable ($\kappa = 0.88$) to the present study results ($\kappa = 0.81$-0.88). The clinical performance of the model in the current study was relatively reliable; however, this was partly because the generated image was used as part of the overall MRI protocol. Further improvement could be achieved by using a more specific GAN model for MRI. Yu et al.[22] used an edge-aware GAN for generating cross-modality MRI, and this model was focused on textural details of the MR sequence, unlike other models that mainly considered minimizing the pixel-intensity difference.[22]

Another recent study attempted to synthesize fat-saturated T2-WI from T1 and T2-WI of the spine.[23] They utilized the Bloch equation, which calculates the contrast difference between individual sequences. In their study, the GAN based on the Bloch equation learned the relationship between T1-, T2-, and fat-saturated T2-WI and then it generated fat-saturated T2-WI from T1- and T2-WI. According to their study, the generated images showed SSIM values of 0.8321-0.8570 and PSNR values of 28.1150-29.1085 dB. In comparison, the present study showed a relatively low SSIM value of 0.4781. As mentioned above, this was partly due to the use of a different deep learning model in the study. In addition, it can be inferred that MRI synthesis based on multiple contrast images strongly contributed to the accurate results, as the previous study generated fat-saturated T2 images from two different sequences, T1- and T2-WI.[23]

An interesting finding of this study was that the diagnostic accuracy of the normal joint state (WNL and absence of effusion) was lower than that of joints with pathology. This was probably due to the contrast similarity between cortical bone and disc in PD-WI. In the TMJ MRI protocol, PD- or T1-WI is mainly used to diagnose disc malposition.[1-3] In a normal joint, the disc is sometimes difficult to identify, as it is located between the cortex of the mandibular condyle and articular eminence in PD image. When the disc is displaced, it is completely surrounded by soft tissues only and is rather clearly visible. Likewise, if there is joint effusion, the disc is isolated from the surrounding cortex, making it easier to identify both the exudate and the disc than in the normal state. As a result, image synthesis based on two or more different contrasts of MRI would be expected to improve model performance, as was tried in previous studies.[23]

The present study had some limitations. First, the image data used in this study were not perfectly identical pairs. In other words, we could not perform registration between individual sequences, although this is considered to be an important pre-processing step for image generation. Kim et al. also mentioned that an absence of registration across the different MR sequences was a limitation of their study of the MRI quality improvement based on a GAN.[21] The image data used in the current study were obtained in parasagittal sections with 2.5-mm slice thickness. This was not sufficient for 3-dimensional registration across the different sequences. Second, the model was trained with an image data set from only one institution. Since there are many other TMJ protocols of different institutions with varied imaging parameters, the direct application of the model would show different results from those of the present study. Further research with more sophisticated and heterogeneous image data preparation would contribute to improved results.

As MRI is the proper modality for TMJ disease patients with disc pathology, the time taken for the examination is always considered as a limitation. Therefore, in patients with pain or restrictions in mouth opening, synthetic T2-

WI would be beneficial. The current study suggests that the application of pT2 images with PD-WI was useful for TMJ diagnosis, although the image quality of pT2 was not fully satisfactory. Adoption of pT2 is carefully suggested for patients from whom it is difficult to obtain the whole imaging series. Additionally, further research should develop methods for more accurately synthesizing T2-WI.

Conflicts of Interest: None

References

1. Tomas X, Pomes J, Berenguer J, Quinto L, Nicolau C, Mercader JM, et al. MR imaging of temporomandibular joint dysfunction: a pictorial review. Radiographics 2006; 26: 765-81.
2. Navallas M, Inarejos EJ, Iglesias E, Cho Lee GY, Rodríguez N, Antón J. MR imaging of the temporomandibular joint in juvenile idiopathic arthritis: technique and findings. Radiographics 2017; 37: 595-612.
3. Tokuda O, Harada Y, Shiraishi G, Motomura T, Fukuda K, Kimura M, et al. MRI of the anatomical structures of the knee: the proton density-weighted fast spin-echo sequence vs the proton density-weighted fast-recovery fast spin-echo sequence. Br J Radiol 2012; 85: e686-93.
4. Lustig M, Donoho D, Pauly JM. Sparse MRI: the application of compressed sensing for rapid MR imaging. Magn Reson Med 2007; 58: 1182-95.
5. Hollingsworth KG. Reducing acquisition time in clinical MRI by data undersampling and compressed sensing reconstruction. Phys Med Biol 2015; 60: R297-322.
6. Shin Y, Yang J, Lee YH. Deep generative adversarial networks: applications in musculoskeletal imaging. Radiol Artif Intell 2021; 3: e200157.
7. Hwang JJ, Jung YH, Cho BH, Heo MS. Very deep super-resolution for efficient cone-beam computed tomographic image restoration. Imaging Sci Dent 2020; 50: 331-7.
8. Yang G, Yu S, Dong H, Slabaugh G, Dragotti PL, Ye X, et al. DAGAN: deep de-aliasing generative adversarial networks for fast compressed sensing MRI reconstruction. IEEE Trans Med Imaging 2018; 37: 1310-21.
9. Mori M, Fujioka T, Katsuta L, Kikuchi Y, Oda G, Nakagawa T, et al. Feasibility of new fat suppression for breast MRI using pix2pix. Jpn J Radiol 2020; 38: 1075-81.
10. Gao F, Xu X, Yu J, Shang M, Li X, Tao D. Complementary, heterogeneous and adversarial networks for image-to-image translation. IEEE Trans Image Process 2021; 30: 3487-98.
11. Xia Y, Zhang L, Ravikumar N, Attar R, Piechnik SK, Neubauer S, et al. Recovering from missing data in population imaging - cardiac MR image imputation via conditional generative adversarial nets. Med Image Anal 2021; 67: 101812.
12. Wang Z, Bovik AC, Sheikh HR, Simoncelli EP. Image quality assessment: from error visibility to structural similarity. IEEE Trans Image Process 2004; 13: 600-12.
13. Mason A, Rioux J, Clarke SE, Costa A, Schmidt M, Keough V, et al. Comparison of objective image quality metrics to expert radiologists' scoring of diagnostic quality of MR images. IEEE Trans Med Imaging 2020; 39: 1064-72.
14. Boulanger M, Nunes JC, Chourak H, Largent A, Tahri S, Acosta O, et al. Deep learning methods to generate synthetic CT from MRI in radiotherapy: a literature review. Phys Med 2021; 89: 265-81.
15. Park JW, Song HH, Roh HS, Kim YK, Lee JY. Correlation between clinical diagnosis based on RDC/TMD and MRI findings of TMJ internal derangement. Int J Oral Maxillofac Surg 2012; 41: 103-8.
16. Gonçalves FG, Serai SD, Zuccoli G. Synthetic brain MRI: review of current concepts and future directions. Top Magn Reson Imaging 2018; 27: 387-93.
17. Tanenbaum LN, Tsiouris AJ, Johnson AN, Naidich TP, DeLano MC, Melhem ER, et al. Synthetic MRI for clinical neuroimaging: results of the magnetic resonance image compilation (MAGiC) prospective, multicenter, multireader trial. AJNR Am J Neuroradiol 2017; 38: 1103-10.
18. Lee SM, Choi YH, Cheon JE, Kim IO, Cho SH, Kim WH, et al. Image quality at synthetic brain magnetic resonance imaging in children. Pediatr Radiol 2017; 47: 1638-47.
19. Lee C, Choi YJ, Jeon KJ, Han SS. Synthetic magnetic resonance imaging for quantitative parameter evaluation of temporomandibular joint disorders. Dentomaxillofac Radiol 2021; 50: 20200584.
20. Benzakoun J, Deslys MA, Legrand L, Hmeydia G, Turc G, Hassen WB, et al. Synthetic FLAIR as a substitute for FLAIR sequence in acute ischemic stroke. Radiology 2022; 303: 153-9.
21. Kim KH, Do WJ, Park SH. Improving resolution of MR images with an adversarial network incorporating images with different contrast. Med Phys 2018; 45: 3120-31.
22. Yu B, Zhou L, Wang L, Shi Y, Fripp J, Bourgeat P. Ea-GANs: edge-aware generative adversarial networks for cross-modality MR image synthesis. IEEE Trans Med Imaging 2019; 38: 1750-62.
23. Kim S, Jang H, Hong S, Hong YS, Bae WC, Kim S, et al. Fat-saturated image generation from multi-contrast MRIs using generative adversarial networks with Bloch equation-based autoencoder regularization. Med Image Anal 2021; 73: 102198.