

Method for motion artifact reduction using a convolutional neural network for dynamic contrast enhanced MRI of the liver

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Purpose: To improve the quality of images obtained via dynamic contrast-enhanced MRI (DCE-MRI) that include motion artifacts and blurring using a deep learning approach.

Methods: A multi-channel convolutional neural network (MARC) based method is proposed for reducing the motion artifacts and blurring caused by respiratory motion in images obtained via DCE-MRI of the liver. The training datasets for the neural network included images with and without respiration-induced motion artifacts or blurring, and the distortions were generated by simulating the phase error in k-space. Patient studies were conducted using a multi-phase T1-weighted spoiled gradient echo sequence for the liver containing breath-hold failures during data acquisition. The trained network was applied to the acquired images to analyze the filtering performance, and the intensities and contrast ratios before and after denoising were compared via Bland–Altman plots.

Results: The proposed network was found to significantly reduce the magnitude of the artifacts and blurring induced by respiratory motion, and the contrast ratios of the images after processing via the network were consistent with those of the unprocessed images.

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Conclusion: A deep learning based method for removing motion artifacts in images obtained via DCE-MRI in the liver was demonstrated and validated.

KEYWORDS

deep learning, *motion artifact*, DCE-MRI, liver imaging

1 | INTRODUCTION

Dynamic contrast enhanced MRI (DCE-MRI) in the liver is widely used for detecting hepatic lesions and in distinguishing malignant from benign lesions. However, such images often suffer from motion artifacts due to unpredictable respiration, dyspnea, or mismatches in k-space caused by rapid injection of the contrast agent[1][2]. In DCE-MRI, a series of T1-weighted MR images is obtained after the intravenous injection of a gadolinium-based MR contrast agent, such as gadoxetic acid. However, acquiring appropriate data sets for DCE arterial phase MR images is difficult due to the limited scan time available in the first pass of the contrast agent. Furthermore, it has been reported that transient dyspnea can be caused by gadoxetic acid at a non-negligible frequency [1][2], which results in degraded image quality due to respiratory motion-related artifacts.

Recently, many strategies have been proposed to avoid motion artifacts in DCE-MRI. Of these, fast acquisition strategies using compressed sensing may provide the simplest way to avoid motion artifacts in the liver [3][4][5]. Compressed sensing is an acquisition and reconstruction technique based on the sparsity of the signal, and the k-space undersampling results in a shorter scan time. Zhang et al. demonstrated that DCE-MRI with a high acceleration factor of 7.2 using compressed sensing provides significantly better image quality than conventional parallel imaging [4]. Other approaches include data acquisition without breath holding (free-breathing method) using respiratory triggering and respiratory triggered DCE-MRI, which is an effective technique to reduce motion artifacts in cases of patients who are unable to suspend their respiration [6][7]. In these approaches, sequence acquisitions are triggered based on respiratory tracings or navigator echoes, and typically provide a one-dimensional projection of abdominal images. Shreyas et al. found that the image quality in acquisitions with navigator echoes under free-breathing conditions is significantly improved. Although triggering based approaches successfully reduce the motion artifacts, it is not possible to appropriately time arterial phase image acquisition due to the long scan times required to acquire an entire dataset. In addition, miss-triggers often occur in cases of unstable patient respiration, which causes artifacts and blurring of the images. Recently, a radial trajectory acquisition method with compressed sensing was proposed [8][9], which enables high-temporal resolution imaging without breath holding in DCE-MRI. However, the image quality of radial acquisition without breath holding is worse than that with breath holding even though the clinical usefulness of radial trajectory acquisition has been demonstrated in many papers [10][11].[12]

Post-processing artifact reduction techniques using deep learning approaches have been also been proposed. Deep learning, which is used in complex non-linear processing applications, is a machine learning technique that relies on a neural network with a large number of hidden layers. Han et al. proposed a denoising algorithm using a multi-resolution convolutional network called “U-Net” to remove the streak artifacts induced in images obtained via radial acquisition [13]. In addition, aliasing artifact reduction has been demonstrated in several papers as an alternative to compressed sensing reconstruction [14][15][16]. The results of several feasibility studies of motion artifact reduction in the brain [17][18][19], abdomen [20], and cervical spine [21] have also been reported. Although these post-processing techniques has been an objective of study for a long time, no studies have ever demonstrated the practical artifact reduction for the

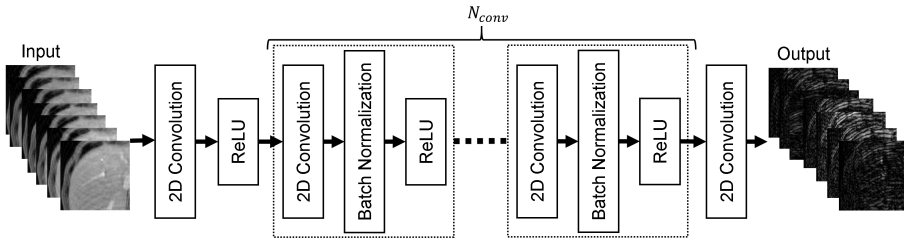


FIGURE 1 Network architecture for the proposed convolutional neural network, two-dimensional convolutions, batch normalizations, and ReLU. The network predicts the artifact component from an input dataset. The network number of convolution layers was determined by simulation-based method.

DCE-MRI of the liver.

In this study, a motion artifact reduction method was developed based on a convolutional network (MARC) for DCE-MRI of the liver that removes motion artifacts from input MR images. Both simulations and experiments were conducted to demonstrate the validity of the proposed algorithm.

2 | METHODS

2.1 | Network architecture

In this paper, a patch-wise motion artifact reduction method that employs a convolutional neural network with multi-channel images (MARC) is proposed, as shown in Fig. 1, which is based on the network originally proposed by Zhang et al. for Gaussian denoising, JPEG deblocking, and super-resolution of natural images. The network relies on two-dimensional convolutions, batch normalizations, and rectified linear units (ReLU) to extract artifact components from images with artifacts. The input to the network is a seven-layer patched image. In the first layer, 64 filters using a kernel size of 3×3 in ReLU were adopted to facilitate non-linear operation. The number of convolution layers N_{conv} was determined as shown in the Analysis subsection. In the last layer, seven filters with a kernel size of 3×3 were used. Finally, a 7-channel image was predicted as the output of the network. Artifact-reduced images can then be generated by subtracting the predicted image from the input.

2.2 | Imaging

Following Institutional Review Board approval, patient studies were conducted. This study retrospectively included 26 patients (M/F, mean age 63, range 34–79 y.o.) that underwent DCE-MRI of the liver in our institution. MR images were acquired using a 3T MR750 system (GE Healthcare, Waukesha, WI), a whole-body coil and 32-channel torso array were used for RF receiving and transmission, and self-calibrated parallel imaging (ARC) was used with an acceleration factor of 2×2 . A three-dimensional (3D) T1-weighted spoiled gradient echo sequence with a dual-echo bipolar readout and variable density Cartesian undersampling (DISCO: differential subsampling with cartesian ordering) was used for the acquisition [22], along with an elliptical-centric trajectory with pseudo-randomized sorting in ky-kz. A total of seven temporal phase images, including pre-contrast and six arterial phases, were obtained using gadolinium contrast with end-expiration breath-holdings of 10 and 21 s. The acquired k-space datasets were reconstructed using a view-sharing approach between the phases and a two-point Dixon method to separate the water and fat components. The

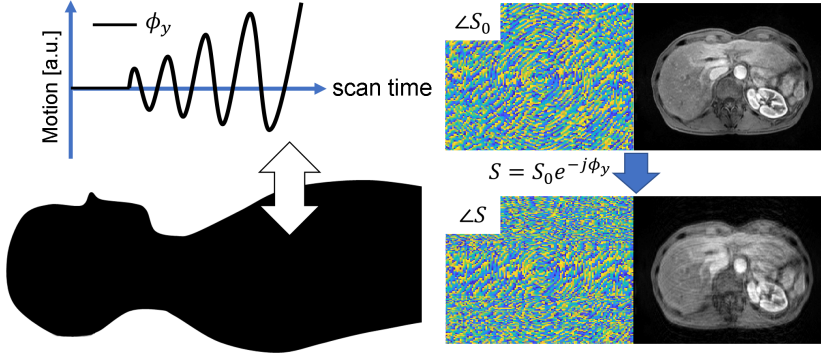


FIGURE 2 (left) Example of a simulation of the respiratory motion artifact by adding phase errors along the phase-encoding direction in k-space. (right) The k-space and image datasets before and after adding simulated phase errors.

following imaging parameters were used: flip angle = 12° , receiver bandwidth = ± 167 kHz, TR = 3.9 ms, TE = 1.1/2.2 ms, acquisition matrix size = 320×192 , FOV = 340×340 mm², the total number of slices = 56, slice thickness = 3.6 mm. The acquired images were cropped to a matrix size of 320×280 after zero-filling to 320×320 .

2.3 | Respiration-induced noise simulation

A respiration-induced artifact was simulated by adding periodic noise to the acquired k-space datasets. Generally, a breath-holding failure causes noise in particular k-space data points. In this study, for simplicity, rigid motion was assumed in the direction perpendicular to the slice, as shown in Fig. 2. In this case, the phase error was induced in the phase-encoding direction, and was proportional to the motion shift. Then, the MR signal S with phase error ϕ can be expressed as follows:

$$S(k_x, k_y) = S_0(k_x, k_y) e^{-j\phi(k_y)}, \quad (1)$$

where S_0 is the signal without the phase error, k_x, k_y represent the k-space in the readout and phase-encoding directions, respectively.

It was assumed that breath-hold failures occurred after a delay as the scan time proceeded, and the acquisition was conducted using simple centric ordering. The phase error can be expressed as follows:

$$\phi(k_y) = \begin{cases} 0 & (k_y < k_{y0}) \\ \sin(\alpha(k_y - k_{y0})) & (\text{otherwise}), \end{cases}$$

where α is the period of the sine wave, and $k_{y0}, (-\pi < k_{y0} < \pi)$ is the delay time for the phase error.

In this study, the values of α (from 0.1 to 5 Hz) and k_{y0} (from $\pi/10$ to $\pi/2$) were selected randomly.

2.4 | Network Training

The processing was implemented in MATLAB 2018b on a workstation running Ubuntu 16.04 LTS with an Intel Xeon CPU E5-2630, 128 GB DDR3 RAM, and an NVIDIA Quadro P5000 graphics card.

The data processing sequence used in this study is summarized in Fig 3. Training datasets containing artifacts and residual patches were generated using multi-phase magnitude-only reference images ($RO \times PE \times SL \times \text{Phase}$: $320 \times 280 \times 56 \times 7$) acquired from six patients selected by a radiologist from among the 26 patients in the study. The radiologist confirmed that all reference images were successfully acquired without motion artifacts. For the multi-phase slices ($320 \times 280 \times 7$) of the images, 14,190 patches $96 \times 96 \times 7$ in size were randomly cropped. The resulting patches that contained only background signals were removed from the training datasets. Images with motion artifact (artifact images) were generated using the reference images, as explained in the previous subsection. Artifact patches, which were used as inputs to the MARC, were cropped from the artifact images using the same method as that for the reference patches. Finally, residual patches, which were used for the output of the network, were generated by subtracting the reference patches from the artifact patches. All patches were normalized by dividing them by the maximum value of the artifact images.

Network training was performed using a Keras and Tensorflow backend (Google, Mountain View, CA), and the network was optimized using the Adam algorithm with a learning rate of 0.001. The optimization was conducted with a mini-batch of 64 patches. A total of 100 epochs with an early-stopping patience of 10 epochs were completed for convergence purposes and the L1 loss function was used as the residual components between the artifact patches and outputs were assumed to be sparse.

$$Loss(I_{art}, I_{out}) = \frac{1}{N} \sum_i^N \|I_{art} - I_{out}\|_1, \quad (2)$$

where I_{art} represents the artifact patches, I_{out} represents the outputs predicted using the MARC, and N is the number of data points.

The N_{conv} used in the network was determined by maximizing the structural similarity (SSIM) index between the reference and artifact-reduced patches of the validation datasets. Here, the SSIM index is a quality metric used for measuring the similarity between two images, and is defined as follows:

$$SSIM(I_{ref}, I_{den}) = \frac{(2\mu_{ref}\mu_{den} + c_1)(2\sigma_{ref,den} + c_2)}{(\mu_{ref}^2 + \mu_{den}^2 + c_1)(\sigma_{ref}^2 + \sigma_{den}^2 + c_2)}, \quad (3)$$

where, I_{ref} and I_{den} are input and artifact-reduced patches, μ is the mean intensity, σ denotes the standard deviation, and c_1 and c_2 are constants. In this study, the values of c_1 and c_2 were as described in [23].

2.5 | Analysis

To demonstrate the performance of the MARC to reduce the artifacts in the DCE-MR images acquired during unsuccessful breath holding, the following experiments were conducted using the data from the 20 remaining patients in the study. To identify biases in the intensities and liver-to-aorta contrast between the reference and artifact-reduced images, a Bland–Altman analysis, which plots the differences of the two images versus their average, was used in which the intensities were obtained from the central slice in each phase. The Bland–Altman analysis for the intensities

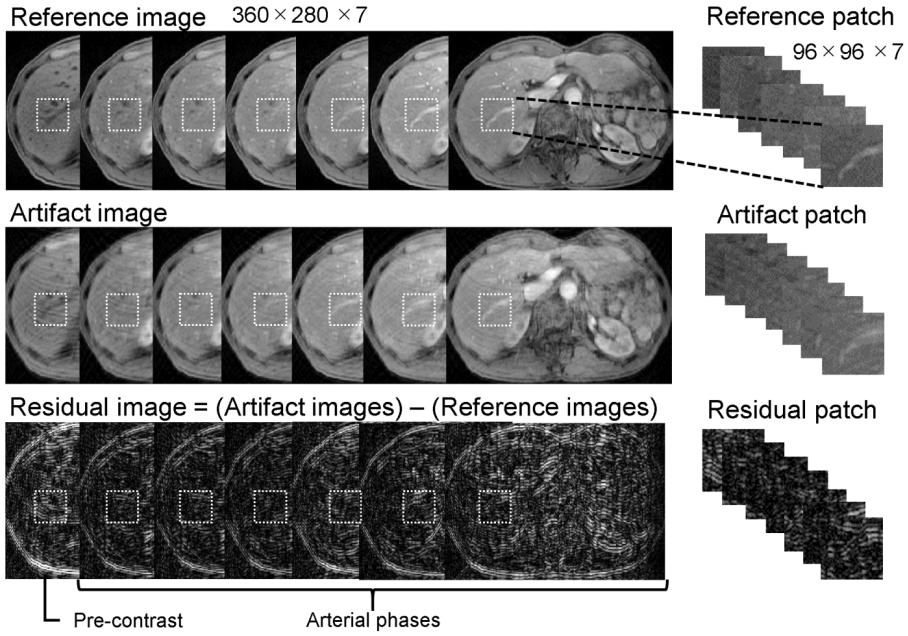


FIGURE 3 Data processing for the training. The artifact images were simulated from the reference images. Residual images were calculated by subtracting the reference patches from the artifact patches. A total of 14,190 patches were generated by randomly cropping small images from the original images.

was conducted in subgroup of high (mean intensity ≥ 0.4) and low (mean intensity < 0.4) intensities. The mean signal intensities of the liver and aorta were measured by manually placing the region-of-interest (ROI) on the MR images, and the ROI of the liver was carefully located in the right lobe to exclude vessels. The same ROIs were applied to all other phases of the images. The quality of images before and after applying the MARC were visually evaluated by a radiologist (M.K.) with three years of experience in abdominal radiology who was not told whether each image came before or after the MARC was applied. The radiologist evaluated the images using a 5-point scale based on the significance of the artifacts (1 = no artifact; 2 = mild artifacts; 3 = moderate artifacts; 4 = severe artifacts; 5 = non-diagnostic).

3 | RESULTS

The changes in the mean and standard deviation (μ) of the SSIM index between the reference and artifact-reduced images are plotted versus N_{conv} in Fig. 4 (a), and the results show that the network with an N_{conv} of more than five exhibited a better SSIM index, while networks with an N_{conv} of five or below had a poor SSIM index. In this study, an N_{conv} of six was adopted in the experiments as this value maximized the SSIM index (mean: 0.87, μ : 0.06). The training was successfully terminated by early stopping in 68 epochs as shown in Fig. 4 (b).

Figures 5 (a) and (b) show the Bland-Altman plots of the intensities and liver-to-aorta contrast ratios between the reference and artifact-reduced images. The differences in the intensities between the two images (mean difference = -0.01 (95 % CI, -0.25-0.01) in mean intensity < 0.4 and mean difference = -0.08 (95 % CI, -0.25-0.01) in mean intensity ≥ 0.4) were heterogeneously distributed, depending on the mean intensity. The intensities of the artifact-reduced images

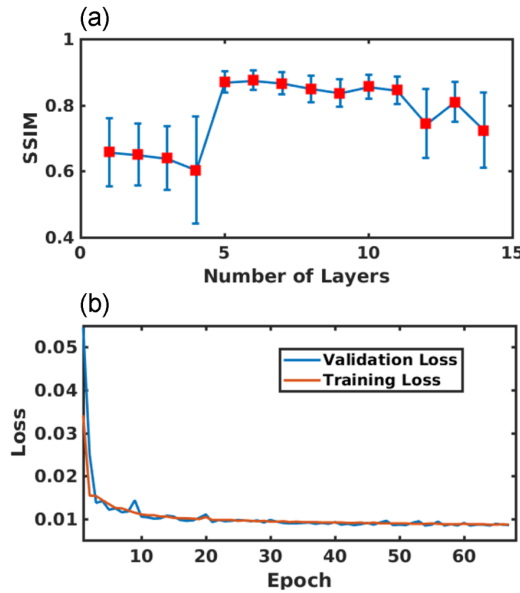


FIGURE 4 (a) SSIM changes depending on the number of layers (N_{conv}). The highest SSIM (0.87) was obtained with an N_{conv} of 6. (b) The L1 loss was decreasing in both training, validation datasets as number of epochs increased. No further decrease was visually observed in > 58 epochs. The training was terminated by early stopping in 68 epochs.

were lower than those of the references by 15 % on average, which can be seen in the high signal intensity areas shown in Fig. 5 (a). A Bland–Altman plot of the liver-to-aorta contrast ratio (Fig. 5 (b)) showed no systematic errors in contrast between the two images.

The image quality of the artifact-reduced images (mean (SD) score = 2.1(1.1)) were significantly better ($P = 0.0025$) than that of the reference images (mean (SD) score = 1.7(0.9)), and the respiratory motion-related artifacts (Fig. 6 top row) were reduced by applying MARC (Fig. 6 bottom row).

4 | DISCUSSION

In this paper, an algorithm to reduce the number of motion-related artifacts after data acquisition was developed using a deep convolutional network, and was then used to extract artifacts from local multi-channel patch images. The network was trained using reference MR images acquired with appropriate breath-holding, and noisy images were generated by adding phase error to the reference images. The number of convolution layers in the network was semi-optimized in the simulation. Once trained, the network was applied to MR images of patients who failed to hold their breath during the data acquisition. The results of the experimental studies demonstrate that the MARC successfully extracted the residual components of the images and reduced the amount of motion artifacts and blurring.

In MRI of the liver, DCE-MRI is mandatory in order to identify hypervascular lesions, including hepatocellular carcinoma [24][25], and to distinguish malignant from benign lesions. At present, almost all DCE-MR images of the liver are acquired with a 3D gradient echo sequence due to its high spatial resolution and fast acquisition time within a single breath hold. Despite recent advances in imaging techniques that improve the image quality [26][27], it remains difficult

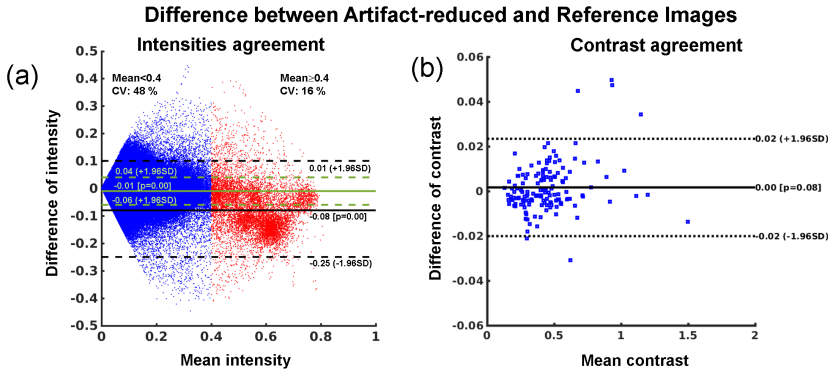


FIGURE 5 Bland-Altman plots for (a) the intensities and (b) the liver-to-aorta contrast ratio between the reference and artifact-reduced images in validation dataset. The mean difference in the intensities was -0.01 (95 % CI, -0.25-0.01) in the parts of mean intensity of < 0.4 and -0.08 (95 % CI, -0.25-0.01) in the parts of mean intensity of ≥ 0.4 . Mean difference in the contrast ratio was 0.00 (95 % CI, -0.02-0.02). These results indicated that there were no systematic errors in the contrast ratios, while the intensities of artifact-reduced images were lower than that of reference images due to the effect of artifact reduction especially in the parts with high signal intensities.

to acquire uniformly high quality DCE-MRI images without respiratory motion-related artifacts. In terms of reducing motion artifacts, the unpredictability of patients is the biggest challenge to overcome as it is not known in advance which patients will fail to hold their breath. One advantage of the proposed MARC algorithm is that it is able to reduce the magnitude of artifacts in images that have been already acquired, which will have a significant impact on the efficacy of clinical MR.

In the current study, an optimal N_{conv} of six was selected based on the SSIM indexes of the reference image and the artifact-reduced image after applying MARC. The low SSIM index observed for small values of N_{conv} was thought to be due to the difficulty of modeling the features of the input datasets with only a small number of layers. On the other hand, a slight decrease and large deviation in the SSIM index were observed for N_{conv} of > 12 . This result implies that overfitting of the network occurred by using too many layers. To overcome this problem, a larger number of learning datasets and/or regularization and optimization of a more complicated network will be required.

Several other network architectures have been proposed for the denoising of MRI images. For example, U-Net [28], which consists of upsampling and downsampling layers with skipped connections, is a widely used fully convolutional network for the segmentation [29], reconstruction, and denoising [30] of medical images. This architecture, which was originally designed for biomedical image segmentation, uses multi-resolution features instead of a max-pooling approach to implement segmentation with high localization accuracy. Most of the artifacts observed in MR images, such as motion, aliasing, or streak artifacts, are distributed globally in the image domain because the noise and errors usually contaminate the k-space domain. It is known that as U-Net has a large receptive field, these artifacts can be effectively removed using global structural information. Generative adversarial networks (GANs) [31], which are comprised of two networks, called the generator and discriminator, is another promising approach for denoising MR images. Yang et al. proposed a network to remove aliasing artifacts in compressed sensing MRI using a GAN-based network with a U-Net generator [15]. Recently, the AUtomated TransfOrm by Manifold APproximation (AUTOMAP) method, which uses full connection and convolution layers, has been proposed for MRI reconstruction [32]. The AUTOMAP method directly transforms the domain from the k-space to the image space, and thus enables highly flexible reconstruction for arbitrary k-space trajectories. These network architectures may be combined to achieve more spatial and temporal

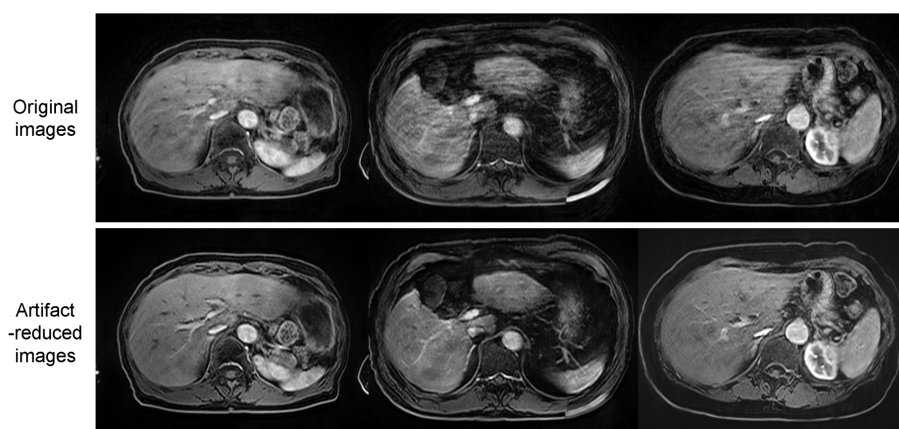


FIGURE 6 Examples of artifact reduction with MARC in a patient from validation dataset. The motion artifacts in the images (upper row) were reduced (lower row) by using the MARC.

resolution. It is anticipated that further studies will be conducted on the use of deep learning strategies in MRI.

The limitations in the current study were as follows. First, clinical significance was not fully assessed. While the image quality appeared to improve in almost all cases, it will be necessary to confirm that no anatomical/pathological details were removed by MARC before this approach can be clinically applied. Second, simple centric acquisition ordering was assumed when generating the training datasets, which means that MARC can only be applied for a limited sequence. Additional training will be necessary before MARC can be generalized to more pulse sequences.

5 | CONCLUSION

In this study, a deep learning-based network was developed to remove motion artifacts in DCE-MRI images. The results of experiments showed the proposed network effectively removed the motion artifacts from the images. These results indicate the deep learning-based network has the potential to also remove unpredictable motion artifacts from images.

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