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Deep Learning With U-Net for Motion Artifact Reduction in Brain MRI

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ABSTRACT

Magnetic Resonance Imaging (MRI) provides detailed three-dimensional visualization of internal structures and plays a crucial role in diagnosing neurological disorders. However, motion artifacts caused by patient movement often degrade image quality and hinder accurate diagnosis. In this study, we propose a U-Net–based deep learning approach to reduce motion artifacts in brain MRI. Standard images without artifacts and motion-corrupted images were obtained from the OpenNeuro database and used to train and evaluate the model. The network was optimized with a fixed learning rate of 0.0001, and performance was assessed using peak signal-to-noise ratio (PSNR) and loss metrics. Experimental results demonstrated a reduction in the loss value from 1.0615 to 0.4424 and an improvement in PSNR from 5.76 to 9.56 after 100 epochs. These findings indicate that the proposed method effectively suppresses motion artifacts and reconstructs brain MRI images with improved diagnostic quality.

KEYWORDS: Brain MRI, Motion artifacts, Deep learning, U-Net.

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INTRODUCTION

Magnetic Resonance Imaging (MRI) is a representative imaging technique capable of precisely evaluating the structure and function of the nervous system, playing an essential role in the accurate diagnosis of neurological disorders in modern medicine(1-2). However, motion artifacts occur in images due to patient respiration, spontaneous body movement, or conditions causing impaired motor control, such as Parkinson's disease or cerebral palsy. These artifacts degrade image quality and act as a major factor hindering accurate diagnosis and appropriate treatment.

Motion artifacts caused by patient or subject movement reduce the spatial consistency and resolution of the images(3). Recent morphological studies using structural MRI have reported that head motion leads to underestimation of cortical thickness and gray matter volume. This demonstrates that head motion can act as a significant confounding factor in neuroimaging studies, complicating interpretation by medical professionals. Therefore, techniques capable of correcting or removing this motion are essential for reliable diagnosis.

Recently, artificial intelligence-based deep learning technology has been actively applied in the medical imaging field, with various studies underway in areas such as diagnostic support, noise reduction, and image quality enhancement(4-5). In particular, U-Net is widely used in medical image segmentation due to its structural advantage of achieving high performance even with relatively small training datasets(6-7). However, existing research primarily focuses on anatomical structure segmentation or disease diagnosis(8), leaving a gap in studies specifically targeting the removal of noise or motion artifacts inherent to the imaging process. Motion artifacts in MRI, in particular, significantly impact diagnostic accuracy, yet attempts to address them using U-Net-based approaches remain insufficient.

Therefore, this study aims to effectively reduce motion artifacts in brain MRI images using a U-Net-based deep learning technique. By training the model on both artifact-free images and images containing artifacts, the goal is to reconstruct images with high diagnostic value, even when artifacts already present during acquisition are present. This is expected to improve image quality, enable accurate diagnosis, and further expand the clinical applicability of deep learning technology in medical image analysis(9).

MATERIALS AND METHODS

1. Related Studies

1.1 Previous Studies

Various approaches have been proposed to minimize motion artifacts in MRI images. Representative techniques include motion correction methods and motion detection algorithms, which are used to correct or remove artifacts within the images. However, limitations have been reported, such as high computational costs and degradation of image quality.

Previous studies have attempted various approaches to detect and correct patient motion(10). However, methods requiring additional equipment like cameras or auxiliary devices were costly, while those involving direct attachment to the patient's head caused discomfort. Furthermore, these techniques necessitate additional hardware and software implementation and demand excessive computational resources, limiting their clinical applicability.

Compressed sensing technology was proposed as another approach to reduce motion artifacts. While this method offers the advantage of optimizing bandwidth for efficient data storage and transmission, it has been noted that the scan time required to acquire the full data set increases, and constraints at the acquisition point can lead to a decline in image quality[11].

Recently, artificial intelligence techniques based on deep learning have gained attention, with active research utilizing U-Net in particular. However, existing studies have been primarily limited to disease classification, lesion detection, and artifact detection, and have not been sufficiently applied to the critical clinical challenge of effectively removing motion artifacts. Consequently, there is a growing need for image restoration research based on U-Net.

1.2 U-Net

U-Net is a deep learning-based image segmentation model first proposed by Ronneberger[12]. This model features a symmetric architecture composed of an encoder and a decoder. The encoder extracts features from the input image, while the decoder utilizes these features to reconstruct the segmentation map. It particularly excels at preserving fine-grained structures and improving segmentation accuracy by effectively combining low-level and high-level features through skip connections between the encoder and decoder.

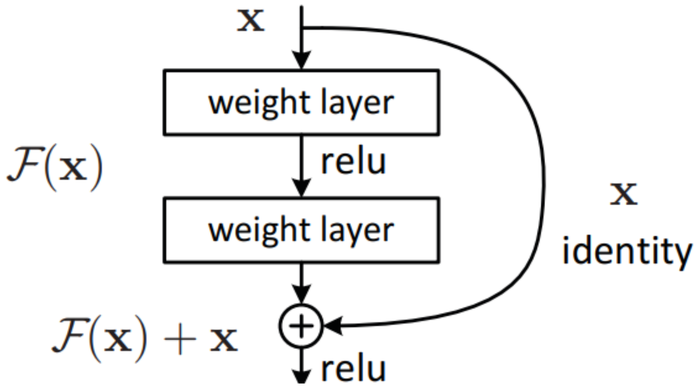

Fig. 1. Residual learning : a building block

U-Net incorporates various structural features, particularly preserving important details through skip connections between the encoder and decoder. These skip connections effectively combine low-level and high-level feature maps, enhancing the accuracy of the final segmentation results. In the final stage, the class of each pixel is determined through an activation function[13].

Furthermore, U-Net enables effective learning even with relatively small datasets and has demonstrated excellent performance in medical imaging. Specifically, its feature fusion utilizing skip connections and its precise segmentation capability of intricate structures have established U-Net as a model optimized for medical image segmentation.

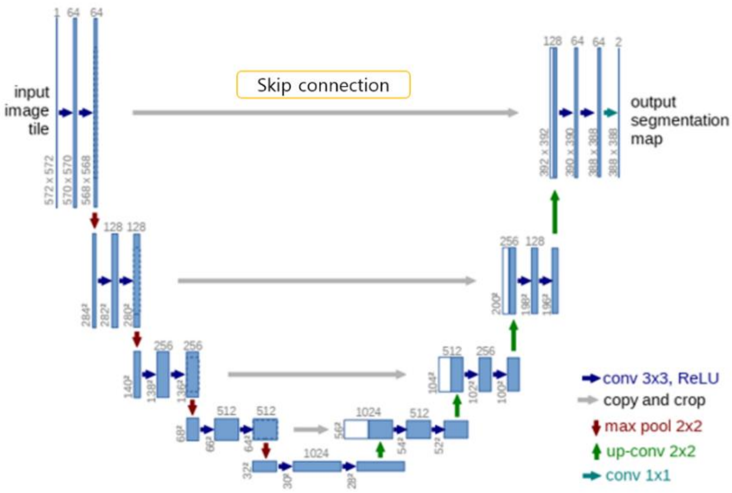

Fig. 2. Structure of 2D U-Net mode

1.3 Inverse Problem

An inverse problem refers to the process of reconstructing the original information of a system or process based on observed data. It typically arises when the characteristics of the system are not precisely known or when it is difficult to solve the known transformation equation in reverse[14].

In medical imaging, inverse problems are utilized to reconstruct detailed original structures from image data or to generate high-quality images by correcting artifacts and incomplete data. These characteristics play a crucial role in enhancing the diagnostic value and clinical utility of images.

The removal of motion artifacts from brain MRI images addressed in this study can also be expressed as an inverse problem (Eq. 2.1). Here, x is the original data (Ground Truth) to be restored, y is the observed image containing artifacts, A is the operator, and v is noise. This study aims to simultaneously achieve artifact suppression and original image restoration by setting the difference between x and y as the objective function for training the U-Net.

Y = A(x)+n (1)

2.1 U-Net-Based Network Design

A U-Net-based deep learning architecture was constructed to reduce motion artifacts in brain MRI images. Input images underwent normalization and resizing. Data augmentation techniques, such as horizontal and vertical flipping, were additionally applied to the training data. Conversely, only normalization and resizing were performed on the test data to maintain consistency in evaluation.

During model implementation, the U-Net architecture was defined. A data loader was constructed using the Custom Dataset class for data input and output. The loss function employed Mean Squared Error (MSE), suitable for image denoising.

$$\Theta^* = \arg\min_{\Theta} \frac{1}{N} \sum_{i=1}^{N} L(F(y_i;\Theta),\xi) + \frac{\lambda}{2}\|\Theta\|^2 \quad (2)$$

2.2 Experimental Protocol

An experimental protocol was established to train the U-Net model based on the acquired data. The entire dataset was split into training and validation data, and model training was performed for 100 epochs. For hyperparameter settings, the Adam optimizer was used, and the learning rate was fixed at 0.0001. The loss function applied Mean Squared Error (MSE), suitable for image denoising.

During training, model performance was evaluated on the validation data using Peak Signal-to-Noise Ratio (PSNR). PSNR is a representative metric for quantitatively comparing the quality between the original image and the restored image, and the loss value was used as a measure indicating the progress of model optimization during training(15). Furthermore, the theoretical background related to loss function selection was referenced from prior studies(16).

Finally, the performance of the U-Net model trained using the test dataset was evaluated. The effectiveness of reducing motion artifacts in brain MRI images was confirmed through visual results and quantitative analysis.

$$MSE = \frac{\sum_{M,N}\left[I_1(m,n) - I_2(m,n)\right]^2}{M * N} \quad (3)$$

$$PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right) \quad (4)$$

2.3 Experimental Setup

This study utilized brain MRI data acquired at the Brain Imaging Centre, Research Centre for Natural Sciences and made publicly available on OpenNeuro. The dataset consists of T1-weighted 3D brain MRI images from 61 healthy adults, including images acquired under three conditions: Standard (no head motion), Head Motion 1 (H1), and Head Motion 2 (H2). Resolution and sequence information were consistently maintained during data collection to ensure the accuracy and reliability of the study.

For model training, each MRI dataset was converted into 183 2D cross-sectional images. The entire dataset was split into training (70%) and validation (30%) sets. The learning rate was fixed at 0.0001, and training was performed for a total of 100 epochs.

RESULTS

1. Model Performance Evaluation

The performance of the proposed U-Net model was evaluated using brain MRI images acquired under Standard, H1, and H2 conditions. A total of 183 2D cross-sectional images were compiled, including 61 image pairs per acquisition condition. Of these, 70% were used for training and 30% for validation. Model training was performed with a learning rate of 0.0001 over 100 epochs.

Evaluation results confirmed that the proposed model generated higher-quality images, with the PSNR value increasing by approximately 63.2% from an initial 5.76 to 9.56. Furthermore, the loss value decreased by approximately 57.4% from 1.0615 to 0.4424, demonstrating that the model effectively minimized the objective function during training.

Visual Assessment

The application of the U-Net-based model effectively removed motion artifacts from brain MRI images. The normal brain MRI images presented in Figure 3 exhibit high resolution and clear structures. The images restored using the proposed model also show suppressed artifacts, revealing more natural and distinct brain structures.

Fig. 3**.** Comparison of brain MRI images before and after applying the proposed U-Net model. The reference image on the left shows normal brain structures without artifacts. The middle image exhibits blurred and distorted cortical boundaries due to head motion. The restored image on the right demonstrates that the proposed model effectively removes artifacts, clearly preserving anatomical structures and presenting a more natural brain structure.

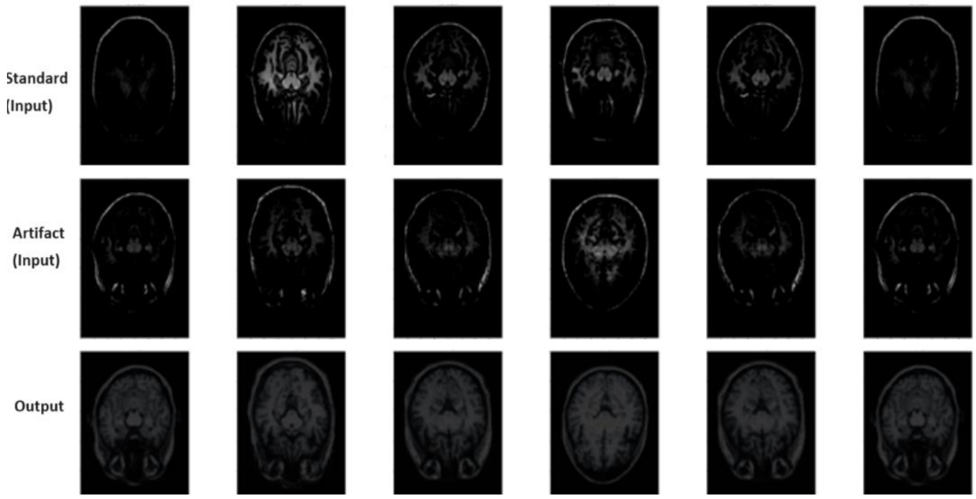

Fig. 3. Brain MRI reconstruction after 50 epochs

Fig. 4. Comparison of brain MRI reconstruction images across training epochs. The image reconstructed at 50 epochs shows reduced artifacts, but residual blurring and structural distortion remain observable around cortical regions. In contrast, the image restored at 100 epochs shows more effectively suppressed artifacts and clearer anatomical boundaries, demonstrating improved image quality as the model progresses through training.

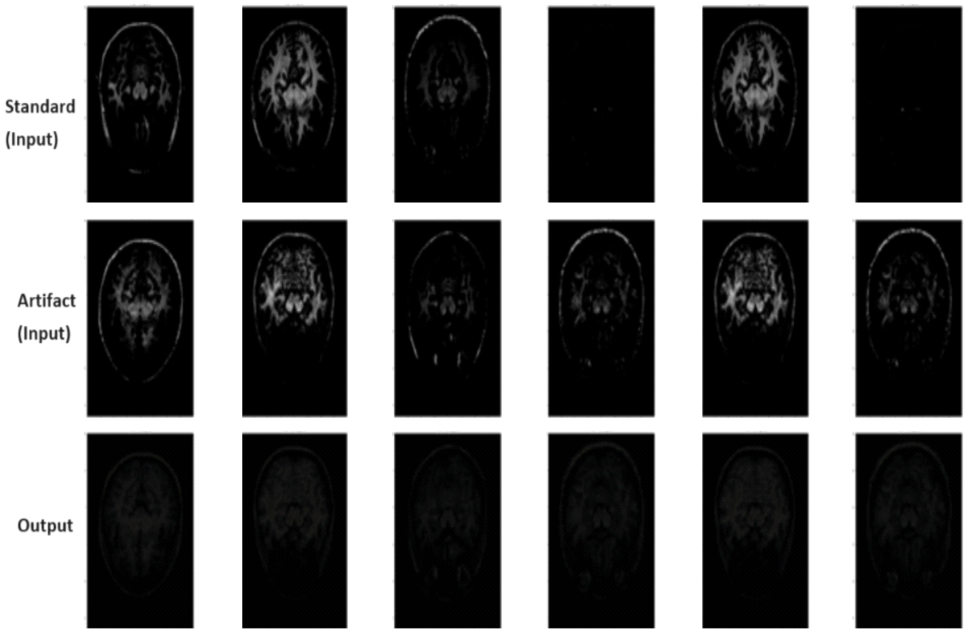

Fig. 4. Brain MRI reconstruction after 100 epochs

Fig. 5. Performance evaluation results of the U-Net model during training. The PSNR value steadily increased with epoch progression, demonstrating the gradual improvement in the quality of the reconstructed images. Simultaneously, the loss value decreased steadily, confirming that the model effectively minimized reconstruction errors. These results suggest that the proposed model exhibits stable convergence characteristics during training, suppressing motion artifacts while preserving anatomical details.

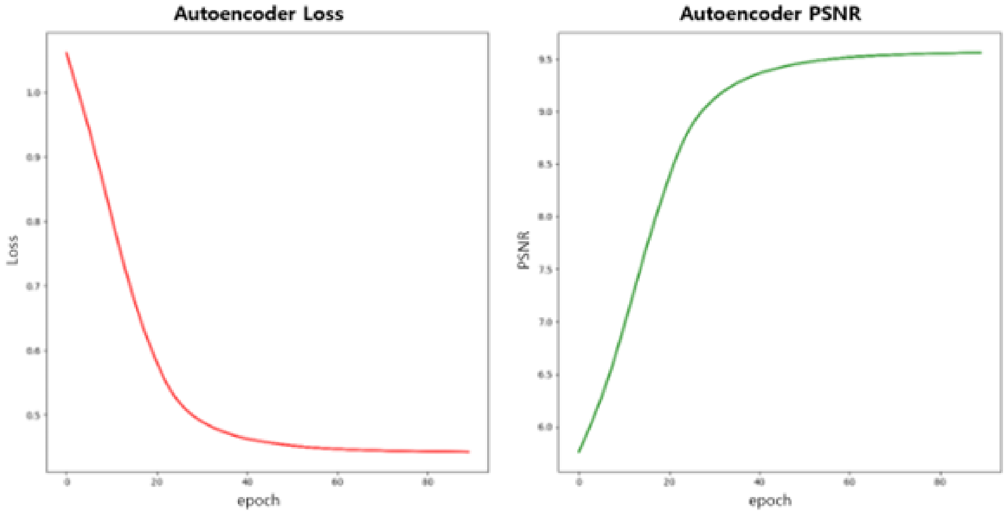

Fig. 5. Changes in PSNR and loss during training

DISCUSSION

This study validated the effectiveness of reducing motion artifacts in brain MRI images using a U-Net-based deep learning model. Experimental results showed that the loss value continuously decreased during training while the PSNR value significantly improved, demonstrating that the proposed model can generate restored images close to the original. These results represent a meaningful achievement, especially considering the limitations of existing motion correction techniques or compressed sensing-based approaches in computational cost, patient discomfort, and image quality degradation.

Notably, the proposed U-Net model demonstrated stable performance even with limited training data, confirming that multi-level feature fusion via skip connections effectively contributes to motion artifact removal. This suggests that the strengths of the U-Net architecture extend beyond simple segmentation and are sufficiently applicable to image restoration. Furthermore, the results of this study demonstrate that AI-based image post-processing technology can contribute to improving the quality of clinical MRI images and enhancing diagnostic accuracy.

However, this study has several limitations. First, the experimental data was limited to T1-weighted 3D brain MRI images provided by OpenNeuro, failing to include diverse image sequences or pathological data. Second, the performance evaluation metrics used only PSNR and loss values; the lack of utilization of subjective image quality assessment metrics such as SSIM (Structural Similarity Index) is regrettable. Third, due to the constraints of the hardware performance used for model training, large-scale dataset training and high-resolution image processing were limited.

Future research should validate the model's versatility by including diverse image sequences and real patient data. Furthermore, a more comprehensive performance evaluation should be conducted using various image quality metrics such as SSIM and FSIM, alongside PSNR. Additionally, it is necessary to validate the relative performance of the U-Net model through comparative studies with state-of-the-art deep learning techniques like Residual Dense Networks and Generative Adversarial Network (GAN)-based restoration models. Such follow-up research could lead to the development of a practical AI-based image correction system applicable in clinical settings.

CONCLUSION

This study proposed a method to effectively reduce motion artifacts in brain axial MRI images by applying a U-Net-based algorithm. Experimental results confirmed that the proposed model significantly suppresses artifacts within images, as evidenced by improvements in PSNR and reductions in loss values. This demonstrates that reducing artifacts generated during the imaging process enables the rapid reconstruction of images with high diagnostic value, suggesting it can further improve the accuracy of brain disease diagnosis and the reliability of medical image analysis.

Future research will aim to extend this algorithm to MRI images containing more diverse training data and complex anatomical structures, with the goal of achieving reconstructed images with high fidelity to the artifact-free original images.

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