Motion Freeze

Head Motion Artifact Correction Technology

TECHNICAL WHITE PAPER

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version

Contents

Introduction

Motion Freeze is an algorithm for head motion artifact correction independently developed by United Imaging, leveraging deep learning technology. The algorithm constructs a large-scale training dataset through the simulation of motion artifacts and then employs deep learning techniques to achieve artifact correction.

Firstly, the algorithm employs real head CT images without motion artifacts. Through a motion model, it simulates head movement in three-dimensional space with varying degrees of rotation, translation, and oscillation, including complex combinations of these motion patterns. This simulation leads to the production of images exhibiting induced motion artifacts. Subsequently, using real images and their corresponding simulated counterparts with artifacts, a comprehensive training dataset consisting of over ten thousand pairs of head images—each pair containing one image with motion artifacts and another without is constructed. Building on this foundation, the Motion Freeze algorithm leverages deep learning techniques to develop a neural network capable of effectively correcting motion artifacts in head CT images.

Benefiting from the network training adequately considering complex head motion patterns and the deep learning network's ability to interpret images globally, the Motion Freeze algorithm can accurately identify and correct motion artifacts in head images. While correcting the motion artifacts, it maintains the normal display of cranial tissue structures.

The following sections will provide an overview of the clinical background of head imaging, outline the challenges in motion artifact correction, then detail the algorithm principles of Motion Freeze, and finally, demonstrate its clinical application outcomes.

Clinical Background

CT has been widely utilized in the clinical diagnosis of various brain conditions, including brain tumors, hydrocephalus, brain hemorrhage, stroke, and trauma. In emergency scenarios, patients may be unable to comply with medical instructions due to factors such as anxiety, medical conditions (e.g., nerve damage, hearing impairment, involuntary tremors in elderly patients, or traumatic pain) [1,2], leading to uncontrollable head movements. These movements often result in motion artifacts, which are a significant cause of failed head imaging procedures.

For patients experiencing head movement during scanning, the scan may be terminated, and the process repeated to obtain images meeting clinical diagnostic requirements. However, re-scanning increases the patient's radiation exposure and the duration of the examination. Correcting motion artifacts in head CT images using algorithms minimizes the need for repeated scans, thereby offering significant clinical application value.

The challenge of motion artifact correction

Researchers have proposed various approaches for correcting motion artifacts.

Some methods involve removing data affected by motion from the raw data [3,4], but this approach is only suitable for scenarios where motion occurs in a continuous and concentrated manner. However, excessive removal of data may negatively impact the quality of image reconstruction.

Literature [5] employs an iterative approach to estimate motion vector sequences, aiming to find a function that represents the strength and influence of motion. Through iterative processes, the method seeks to minimize this function to achieve motion correction. However, the function representing the impact of motion is critical to the correction's effectiveness. Due to the complexity and variability of motion, such a generalized function is challenging to obtain. Additionally, the iterative reconstruction process is highly time-consuming and impractical for clinical applications.

To overcome these limitations, United Imaging adopted a deep learning-based approach for head motion artifact correction. This method leverages deep learning algorithms to address the issue of time-consuming iterative solutions, while employing a motion simulation model to solve the challenge of obtaining a "gold standard" for deep learning algorithms. This approach ensures both the speed of image reconstruction and the correction effect, making it highly significant for clinical applications.

Introduction of Motion Freeze

Motion Freeze is a head motion artifact correction algorithm based on deep learning technology. The algorithm primarily comprises three main components: Construction of the Training Dataset, Construction of the Convolutional Neural Network, and Network Training and Validation.

1. Construction of the Training Dataset

Building an appropriate training dataset is an essential step in deep learning technology. However, in clinical scanning scenarios, obtaining images with motion artifacts and their corresponding artifact-free gold standard images simultaneously is often challenging due to various reasons. The scarcity of such training data has hindered the progress of deep learning-based algorithms for head motion artifact correction.

To tackle this issue, United Imaging introduced an innovative solution [6]. The approach involves using clinical images without motion artifacts as gold standard images. These gold standard images are then subjected to motion artifact simulation to generate images resembling those with motion artifacts observed in clinical scenarios. Through this process, a training dataset consisting of over ten thousand image pairs, each containing one image with motion artifacts and another without has been constructed.

The motion artifact simulation process is illustrated in Figure 1, involves simulating the scanning of three-dimensional motion-free head images in a simulator. During the simulation, random rigid motion is introduced. The data is reconstructed using 3D forward projection and filtered back-projection, resulting in simulated images that contain motion artifacts.

The motion simulation model encompasses common clinical motion patterns, including translational, rotational, oscillatory, and mixed motion modes incorporating multiple patterns. During the simulation, random motion patterns are added at random scanning angles, maximizing the representation of motion's randomness and complexity in clinical scenarios.

The images with motion artifacts, generated through motion simulation as shown in Figure 2, were assessed by radiologists with over five years of experience. Their evaluation indicated that the artifacts closely resemble those seen in clinical scenarios, thus effectively representing the extent of motion artifacts in clinical images.

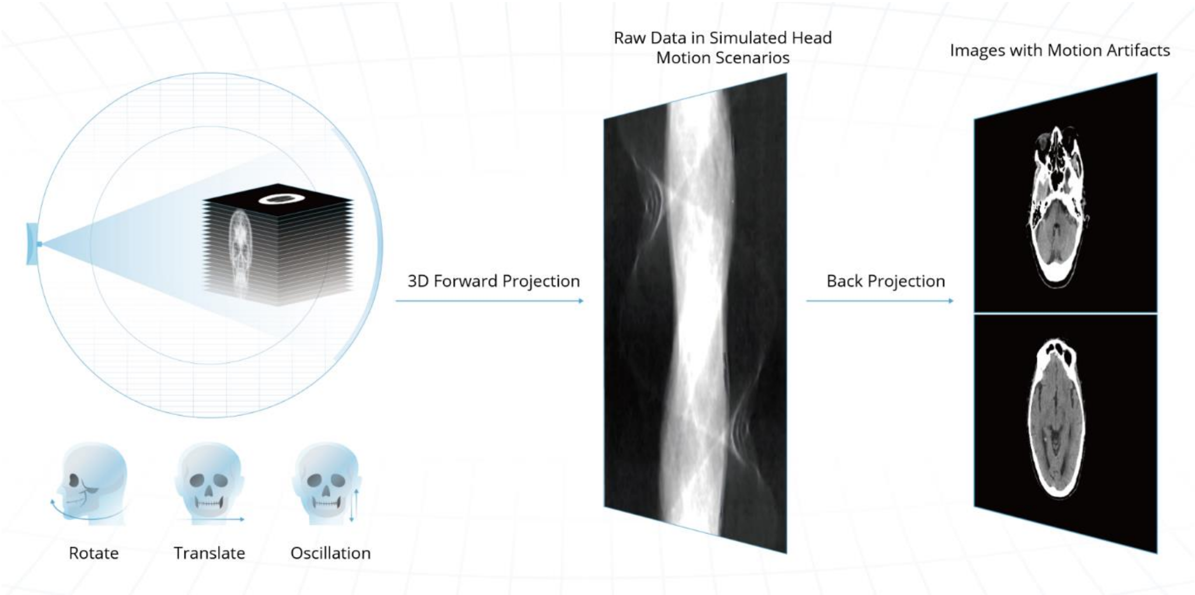


Figure 1. Schematic of Motion Artifact Simulation

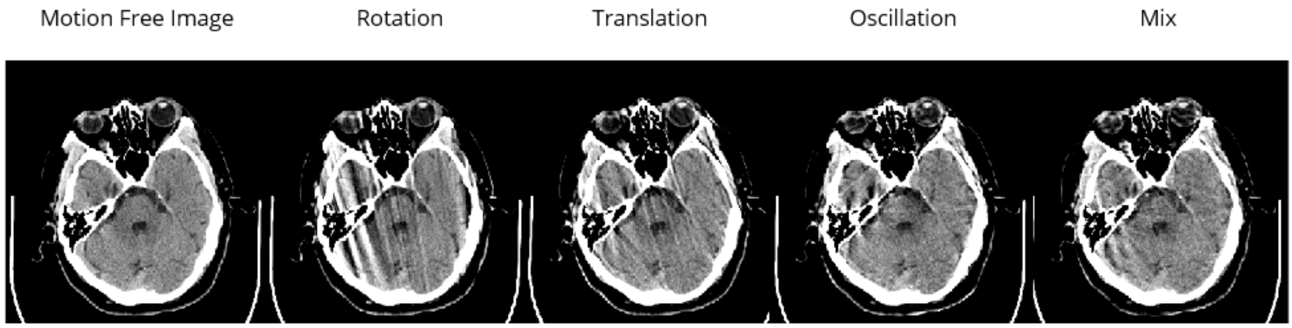


Figure 2. Motion Model-Generated Images with Motion Artifacts

2. Convolutional neural network construction

Neural network construction is a core step in deep learning technology. Only by building an appropriate neural network and continuously training it can the desired outcome of artifact correction be achieved. Motion artifacts caused by head movement often extend over a large area, from the skull outward. Therefore, a larger receptive field in the neural network is necessary to capture more artifact information effectively. In medical image-related deep learning applications, the U-net architecture is often considered. U-net includes downsampling processes, and as downsampling progresses, the receptive field gradually expands, allowing more low-frequency information to be perceived in the image. However, downsampling also leads to a loss of spatial resolution in the image. Consequently, it's essential to preserve spatial resolution during network construction.

Based on these considerations, United Imaging developed a 3D convolutional neural network. Building upon the U-net architecture, they incorporated elements from ResNet. While U-net ensures a large receptive field, the integration of ResNet helps maintain image spatial resolution.

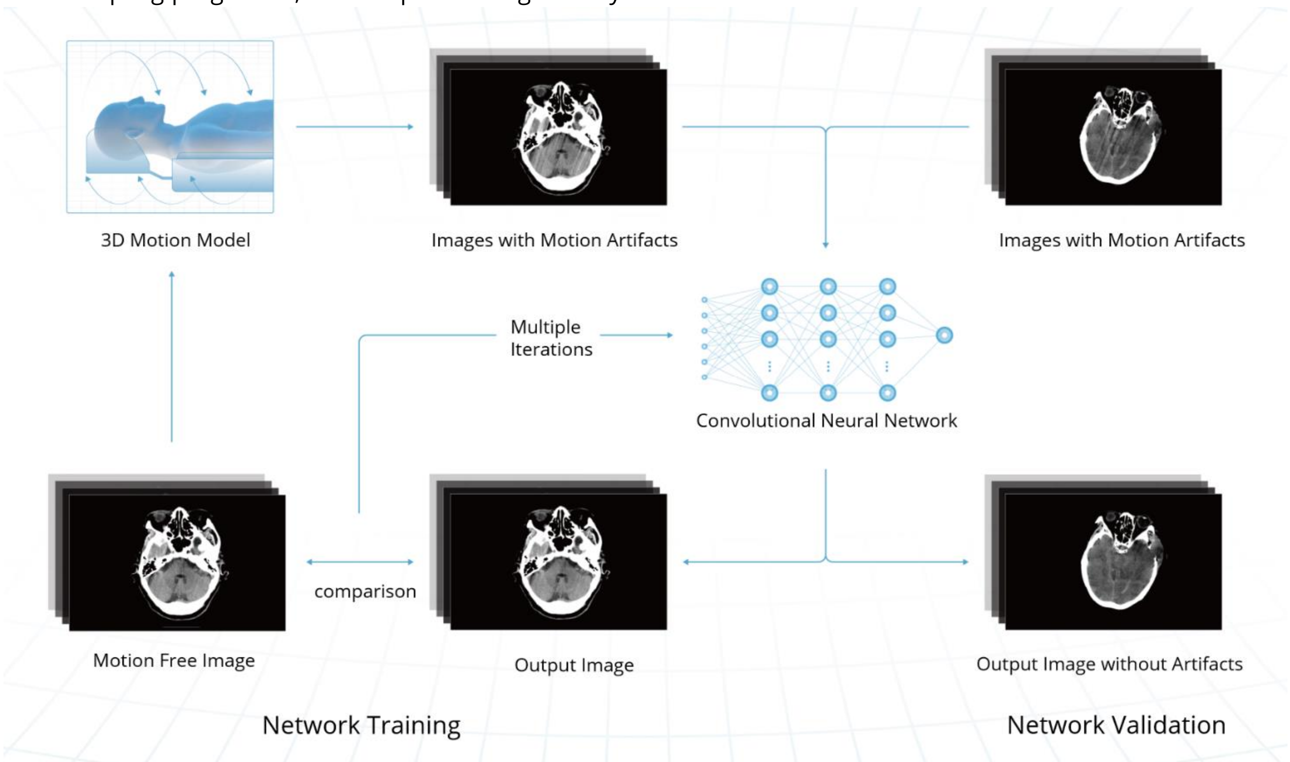


Figure3. Network Training and Validation Process of the Motion Freeze Algorith

3. Network Training and Validation

Using gold-standard data, a 3D motion model is utilized to construct datasets of more than ten thousand image pairs for network training and validation, with the workflow shown in Figure 3.

For network training, input head images containing motion artifacts into the convolutional neural network for correction. Then, compare the output images with the gold-standard images. Re-introduce the output images into the convolutional neural network, continuously adjusting parameters through iteration. As the number of iterations increases, image quality progressively improves. The iterative process concludes when the correction meets the predetermined requirements, yielding the final corrected image.

After completing network training, validate the network's performance using validation dataset images.

For a more comprehensive quantitative assessment, introduce metrics including the Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM) to evaluate clinical image data [7]. MSE reflects the average discrepancy between the corrected and gold-standard images; a smaller value indicates better network performance. PSNR measures image quality, with higher values indicating better quality. SSIM assesses the similarity between two images, considering parameters such as brightness, contrast, and structure; a higher value implies greater similarity. Calculate these metrics for both motion-affected (images with artifacts) and corrected images relative to the gold-standard, with quantitative results presented in Table 1. Compared to motion-affected images, corrected images show significant improvements in MSE, PSNR, and SSIM metrics by 44.1%, 15.8%, and 7.4%, respectively.

Table 1. The quantitative comparison between Motion Image and Corrected Image

	Target	Motion Image	Corrected Image
MSE	0	0.03 ± 0.03	0.01 ± 0.02
PSNR	-	16.89 ± 4.46	19.55 ± 4.27
SSIM	1	0.73 ± 0.08	0.78 ± 0.08

Clinical Applications Evidence

To further demonstrate the performance of Motion Freeze in practical clinical applications, we utilized multiple clinical cases to showcase the advantages of Motion Freeze in motion artifact correction.

Figure 4 presents the head CT images of a 91 - year - old elderly patient. The patient suffered from hearing loss and a head injury. During the first scan, strip-shaped artifacts caused by head movement appeared in the head images, which affected the doctor's diagnosis. To obtain images that met the requirements of clinical diagnosis, a second head scan was conducted on this patient.

The first scanned image with motion artifacts was reconstructed using Motion Freeze. As evaluated by the diagnosing doctor, Motion Freeze could effectively improve the strip-shaped artifacts caused by movement and preserve clear brain structures, achieving an imaging effect comparable to that of the second scan without motion artifact

	type of scan	kV	mAs/mA	$CTDI_{vol}$(mGy)	DLP(mGy*cm)
First scan	Axial	120	347	47.574	761.19
Second scan	Axial	120	297	45.423	726.77

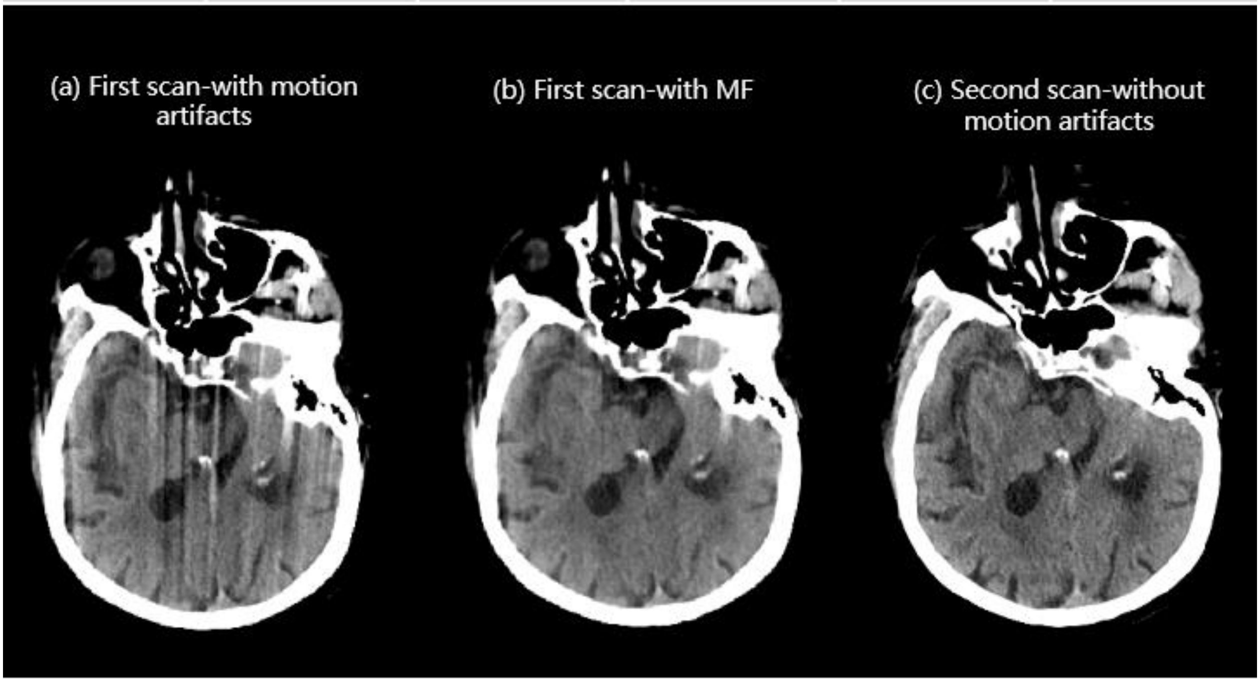


Figure 4. 91-year-old head trauma case. (a) Motion artifacts (first scan), (b) Motion Freeze reconstruction, (c) Artifact-free image (second scan).

Figure 5 illustrates the comparison of corrected and uncorrected images with motion artifacts using transverse, sagittal, and coronal views. In this patient's scans, motion artifacts were evident in the midbrain, temporal lobes, forehead region, and cerebellum at the skull base, impairing diagnostic assessment. Following reconstruction with the Motion Freeze algorithm, the linear artifacts were significantly reduced while preserving brain structure integrity. Radiologists evaluated that the corrected images match the diagnostic quality of artifact-free images, providing enhanced clarity and accuracy for clinical decision-making.

	type of scan	kV	mAs/mA	$CTDI_{vol}$(mGy)	DLP(mGy*cm)
First scan	Axial	120	345	47.503	760.05
Second scan	Axial	120	347	47.779	764.46

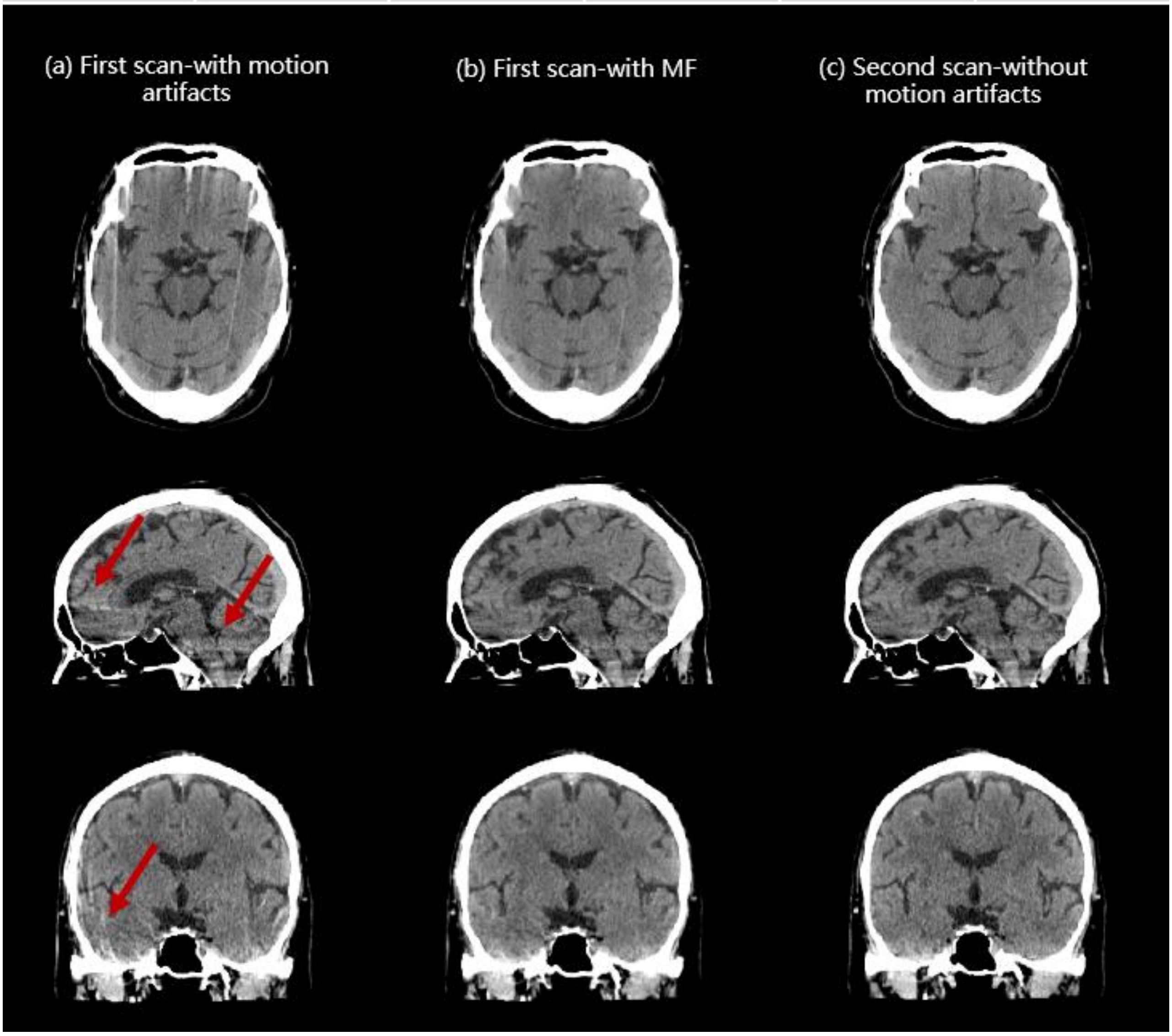
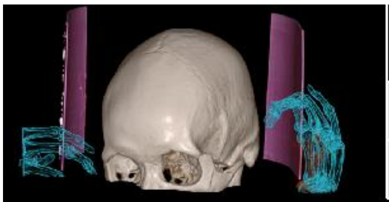


Figure 5. A head trauma case. Top to bottom: axial, sagittal, and coronal head slices; left to right: (a) motion artifact-affected initial scan, (b) Motion Freeze-reconstructed image, (c) follow-up scan without artifacts.

The patient in Figure 6 had severe injuries and was unable to cooperate with the scanning process. Motion artifacts appeared at the skull base during the first scan. To obtain diagnosable images, another scan was conducted with assistance from the patient's family member inside the scanning room to immobilize the patient's head.

As shown in the figure, while this approach eliminated motion artifacts, the family member also received additional radiation dose, and strip-shaped artifacts caused by the hands on both sides were introduced. The image with motion artifacts was reconstructed using Motion Freeze. As evaluated by the diagnosing doctor, Motion Freeze could effectively improve the motion artifacts and provide images that meet the requirements of clinical diagnosis.



	type of scan	kV	mAs/mA	$CTDI_{vol}$(mGy)	DLP(mGy*cm)
First scan	Axial	120	346	47.534	760.54
Second scan	Axial	120	347	47.593	761.48

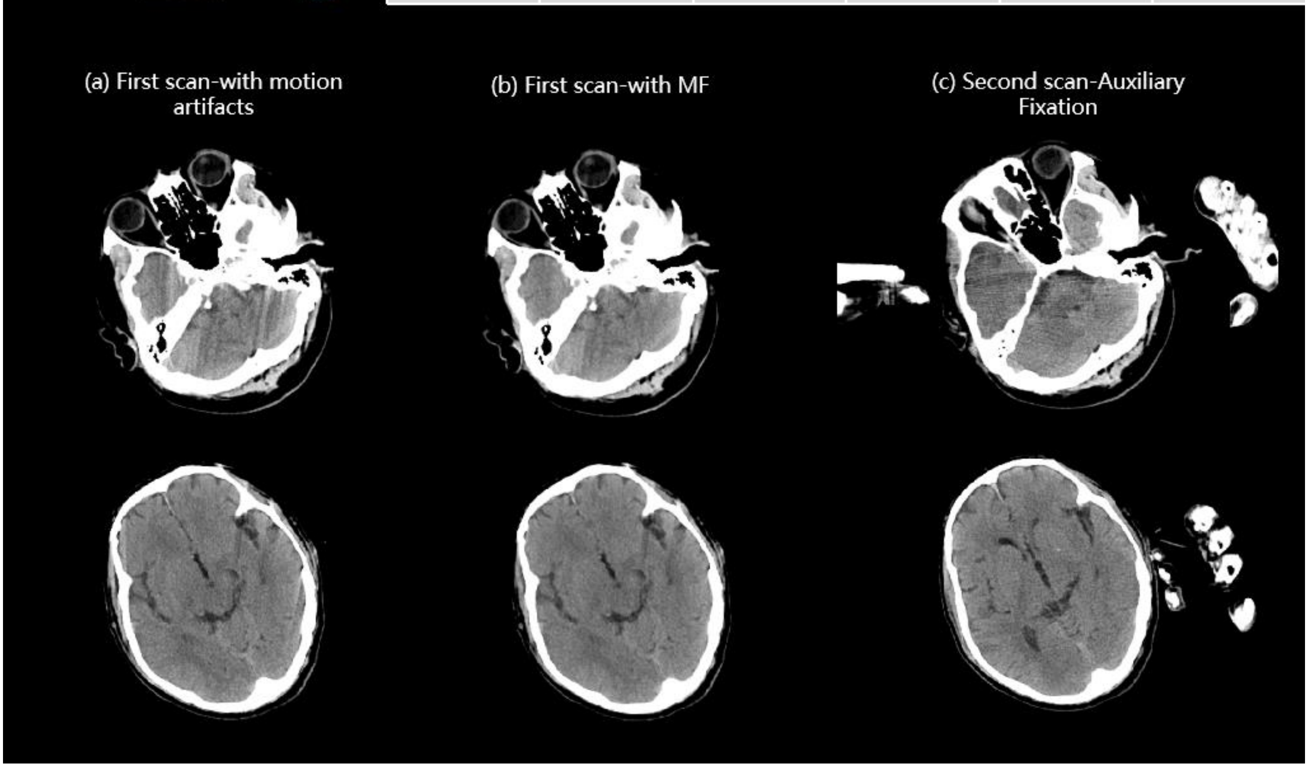


Figure 6. Case of auxiliary fixation: From left to right: (a) Images with motion artifacts after the first scan, (b) Images reconstructed using the Motion Freeze algorithm after the first scan, and (c) Images from the second scan showing no motion artifacts, achieved through family member's auxiliary fixation

Figure 7 presents a CT image of brain perfusion for an 89-year-old patient diagnosed with cerebral ischemia. The perfusion scan indicates a significant reduction in cerebral blood volume (CBV) and cerebral blood flow (CBF) in the left hemisphere, with prolonged mean transit time (MTT) and time to peak (TTP).

The tissue color differentiation shows that the area with relative cerebral blood flow (rCBF) < 30% is smaller than the area with Tmax > 6 s, indicating the presence of an ischemic penumbra. There is still a necessity for thrombolysis or interventional thrombectomy for this patient. During the process of contrast agent inflow, motion artifacts can be seen on the patient's forehead. After reconstruction using the MotionFreeze algorithm, the motion artifacts on the forehead are eliminated. To a certain extent, the application of the Motion Freeze algorithm reduces the likelihood of requiring additional scans for the patient, thereby providing more critical time for treatment and improving their quality of life, while also reducing the burden on both the family and society.

type of scan	kV	mAs/mA	$CTDI_{vol}$(mGy)	DLP(mGy*cm)
Topogram	120	80	0.166	8.91
Axial	100	100	188.195	3011.12

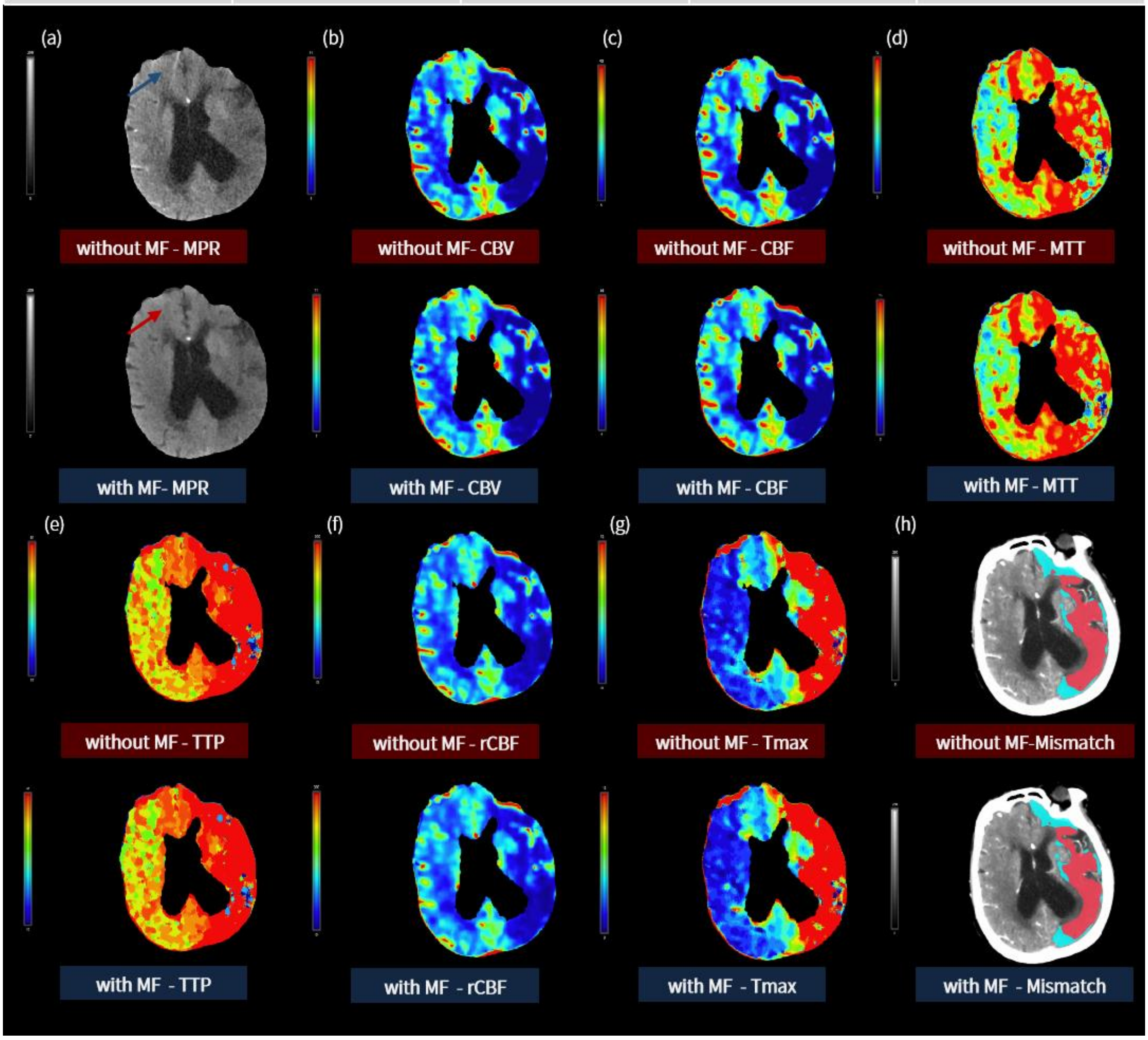


Figure 7. Brain Perfusion Cases. (a)-(h) depict eight groups of brain perfusion images, specifically including Multi-Planar Reconstruction (MPR) images, Cerebral Blood Volume (CBV) images, Cerebral Blood Flow (CBF) images, Mean Transit Time (MTT) images, Time to Peak (TTP) images, Relative Cerebral Blood Flow (rCBF) images, Tmax images, and Mismatch images. Each group comprises two images: the first being the image obtained before applying the Motion Freeze algorithm, and the second being the reconstructed image after Motion Freeze.

Summary

Motion Freeze is a head motion artifact correction technology that first introduced by United Imaging. It employs deep learning technology, which not only overcomes the problem of taking a great deal of time in traditional iterative correction methods, but also ingeniously solves the issue of the difficulty in obtaining gold standard images for deep learning algorithms through the concept of simulating motion artifacts. The introduction of Motion Freeze represents a significant breakthrough in the correction of head motion artifacts.

The Motion Freeze algorithm employs deep learning technology to correct head motion artifacts, substantially improving image quality by mitigating artifacts caused by patient head movements. It minimizes the need for repeated scans and additional radiation exposure while ensuring rapid image reconstruction, making it highly significant in clinical applications.

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