Advances in Magnetic Resonance Imaging Technology

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Abstract. This paper first summarizes the fundamental principles of magnetic resonance imaging (MRI). It then reviews the recent technological advancements of MRI by analyzing the advantages and disadvantages of four types of MRI. The review begins with high-field MRI, analyzing how increased magnetic field strength yields superior image resolution. This enhancement is pivotal for applications such as Alzheimer's research; concurrently, the technology faces technical challenges, including field inhomogeneity. It then discusses real-time functional magnetic resonance imaging (rt-fMRI), a technique offering novel capabilities for studying psychology (e.g., happiness parameters) and neuroscience (e.g., Parkinson's disease). A key limitation, however, is its susceptibility to motion artifacts and interference. The third section delves into the integration of AI with MRI, highlighting its power to reduce the misdiagnosis rate and enhance operational efficiency, while also stressing the critical need for physician oversight, as AI-generated results are not infallible. Finally, the paper examines portable low-field MRI. Due to its low magnetic field and small form factor, it can be equipped in ambulances to save the golden hour for patients. But it has a low signal-to-noise ratio (SNR) problem that needs to be addressed urgently.

INTRODUCTION

MRI is a cornerstone of modern medical diagnostics, utilizing powerful magnetic fields, radio frequency (RF) pulses, and gradient magnetic fields to generate detailed internal images of the body. Initially, MRI presented several key advantages, including safety (as it does not rely on ionizing radiation), non-invasiveness, and superior soft-tissue contrast compared to CT scans. However, early iterations of the technology faced significant challenges, such as low image resolution (making it challenging to display complex structures like the hippocampus), slow imaging speed, limited data processing capabilities, and restricted clinical application due to its large size. To address these limitations, a series of pivotal advancements have been developed in succession, each targeting specific shortcomings. Specifically, high-field MRI enhances the SNR for higher imaging quality. Rt-fMRI, integrating computer technology and algorithms, enables real-time imaging. The integration of AI with MRI leverages deep learning to radically improve data processing capabilities. Through continuous learning from vast amounts of MRI data, AI can be progressively optimized, thereby enhancing diagnostic efficiency and reducing the misdiagnosis rate. For instance, studies have shown that this can increase the efficiency of film reading by about 26% and the detection rate of lung nodules by about 32%. Meanwhile, portable low-field MRI, with its smaller form factor and lower magnetic field strength compared to conventional MRI, has significantly broadened the scope of MRI's application, even enabling simultaneous on-site diagnosis and initial treatment in mobile settings like ambulances, gaining precious time for subsequent intervention.

Since its emergence, MRI has undergone continuous optimization to improve its application value and technical level in medical imaging and other fields. In the 1970s, Mansfield and Lauterbur established the fundamental theory of MRI, paving the way for its subsequent development. This was materialized in 1977 when Raymond Damadian and his team invented the world's first MRI, "Indomitable". The following decades brought rapid innovation: humans created high-field MRI in the late 1980s and early 1990s, followed by the invention of rt-fMRI in the late 1990s, pioneered by Seiji Ogawa. With the swift advancement of information technology, the integration of AI with MRI was realized in the late 2010s, and by 2020, Hyperfine Research successfully applied portable MRI to clinical practice.

Building upon this context, this article is structured as follows: first, it summarizes the basic principles of MRI. Then, it describes the latest progress in high-field MRI, rt-fMRI, the integration of artificial intelligence with MRI, and portable low-field MRI. Lastly, based on an analysis of the current advantages and disadvantages of MRI, this article provides specific guidance for its future development, supported by relevant examples and data.

BASIC PRINCIPLES OF MRI

The Phenomenon of Magnetic Resonance

Nuclear magnetic resonance (NMR) is a physical phenomenon in which atomic nuclei, when placed within a strong, static magnetic field $\boldsymbol{B_0}$, absorb energy from a precisely tuned radiofrequency (RF) pulse. This absorption causes the nuclear spin system to transition between discrete, quantized energy levels.

According to quantum mechanics, the energy difference ΔE between nuclear spin energy levels is directly proportional to the Larmor frequency ω_0, as described by the equation $\Delta E = \hbar\omega_0$, where $\hbar$ is the reduced Planck's constant. For a nucleus to transition from a lower to a higher energy state (a process known as excitation), it must absorb a photon whose energy precisely matches this energy gap. The energy of the incoming RF radiation is given by $E = \hbar\omega$, where ω is the frequency of the applied RF field.

Therefore, the fundamental condition for resonance is met only when the frequency of the RF pulse ω is identical to the Larmor frequency of the nucleus ω_0. The Larmor frequency itself is determined by the external static magnetic field $\boldsymbol{B_0}$ and an intrinsic property of the nucleus, its gyromagnetic ratio γ, according to the formula $\boldsymbol{\omega_0} = \gamma\boldsymbol{B_0}$.

The process of MRI

According to quantum mechanics, the intrinsic spin of an atomic nucleus generates a magnetic moment $\boldsymbol{\mu}$ ($\boldsymbol{\mu} = \gamma\boldsymbol{S}$, where $\boldsymbol{S}$ is the spin angular momentum), causing the nucleus to behave like a microscopic magnet. MRI primarily detects the hydrogen protons ^{1}H, which are abundant in the human body. In the absence of an external magnetic field, the magnetic moments of these protons are randomly oriented, resulting in zero net magnetization. When these nuclei are placed in a strong, static external magnetic field $\boldsymbol{B_0}$, their spin energy levels split (a phenomenon known as Zeeman splitting). For spin-$\frac{1}{2}$ nuclei like protons, the splitting results in two discrete energy levels: a lower-energy "spin-up" state, aligned with $\boldsymbol{B_0}$, and a higher-energy "spin-down" state, anti-aligned with $\boldsymbol{B_0}$. In addition to occupying one of these energy states, each magnetic moment also precesses around the $\boldsymbol{B_0}$ axis at a characteristic Larmor frequency.

According to the Boltzmann distribution ($\frac{N_{down}}{N_{up}} = \exp\left(-\frac{\Delta E}{kT}\right)$, where k is Boltzmann constant, T is absolute temperature), the population of the high-energy state (N_{down}) is slightly less than that of low-energy state (N_{up}). This slight population imbalance creates a small but crucial net macroscopic magnetization $\boldsymbol{M}$ ($\boldsymbol{M} = \frac{\sum \mu_i}{\Delta V}$, where ΔV is volume element, $\sum \boldsymbol{\mu}_i$ is the total magnetic moment in ΔV) aligned with B_0.

However, this longitudinal magnetization $\boldsymbol{M}$ is challenging to detect directly, as the magnetic field $\boldsymbol{B'}$ it generates is orders of magnitude weaker than $\boldsymbol{B_0}$. To overcome this, a radiofrequency (RF) pulse, tuned precisely to the Larmor frequency, is applied to perturb the spin system. This pulse tips the net magnetization vector away from the $\boldsymbol{B_0}$ axis, creating a transverse magnetization component. This new component precesses in the transverse plane and, by Faraday's law of induction, induces a measurable, time-varying electrical signal in a receiver coil.

To form an image, gradient magnetic fields spatially encode the signal by making its Larmor frequency or phase dependent on location. After collecting the resulting composite signal, whose amplitude and decay characteristics are determined by tissue properties such as T1 and T2 relaxation times, a Fourier transformation is applied to reconstruct the spatial signal distribution by mapping the amplitude of each encoded frequency component back to its corresponding spatial origin. This process yields a cross-sectional image where the contrast reflects these underlying tissue property differences.

RECENT ADVANCES IN MRI TECHNOLOGY

Overview of high-field MRI

As the magnetic field strength continues to increase, the SNR is fundamentally boosted, enabling the improvement of MRI image resolution. For instance, while routine clinical scans at 1.5T and 3T can achieve resolutions around 1mm, ultra-high-field systems like 7T can push the in-vivo resolution to the sub-millimeter range, for example, 0.2~0.3mm). High-field MRI, especially ultra-high-field (UHF) MRI, provides clinicians and researchers with more anatomical details and significantly reduces partial volume effect (PVE) in certain areas, thus enhancing the precision of numerous neuroimaging post-processing tasks, such as tissue segmentation and cortical surface reconstruction. High-field MRI can also reveal subtle pathological changes that are invisible to low-field scanners [1]. The improvement of resolution further enhances high-field MRI's application value in research and clinical diagnosis. For example, UHF MRI can be used for observing complex human structures such as the hippocampus, aiding in disease diagnosis and the evaluation of treatment efficacy [1].

The common MRI field strengths used in clinical practice are mainly 1.5T and 3T, with 3T being widely considered the standard for clinical high-field MRI. For research purposes, even higher field strengths, known as UHF MRI, are utilized, such as 7T, 9.4T, and even beyond 10T. However, the widespread adoption of UHF MRI is hindered by significant challenges, including prohibitive costs, complex maintenance, and heightened safety concerns like increased specific absorption rate (SAR). Consequently, the use of UHF MRI is predominantly confined to neuroscience research or specific clinical investigations.

Although high-field MRI provides extremely high SNR and spatial resolution, it still faces two major technical challenges. The first is the inhomogeneity of the main magnetic field ($\mathbf{B_0}$) (more critically at UHF MRI) and the transmit RF field ($\mathbf{B_1}$), which can lead to signal voids and artifacts [2]. The second is the stronger interaction with the metallic implant, especially the UHF MRI [2]. This interaction can cause significant magnetic susceptibility artifacts, which distort the image, and can also lead to tissue heating around the implant, potentially causing unnecessary harm due to RF-induced heating. To address these challenges, a range of solutions are being explored. On the hardware and acquisition front, strategies include advanced shimming techniques to improve field uniformity and sophisticated pulse sequence design (e.g., adjusting the timing, shape, and strength of applied gradient magnetic fields and RF pulses). On the other hand, computational methods are gaining prominence. Researching image processing and deep learning for tasks like artifact correction and image synthesis from low-field to high-field data is also a promising direction to improve imaging quality. In this way, images from lower-field scanners can be computationally enhanced to emulate the quality of images from UHF MRI [1].

Real-time Functional Magnetic Resonance Imaging

Functional magnetic resonance imaging (fMRI) is a non-invasive technique used to evaluate cerebral activity by detecting hemodynamic changes. This method relies on neurovascular coupling: when neuronal activity in a specific brain region increases, there is a corresponding increase in local blood flow. The underlying principle of fMRI is the blood-oxygen-level-dependent (BOLD) contrast, which arises from the magnetic differences between oxygen-rich arterial blood and oxygen-poor venous blood. However, conventional fMRI faces limitations: its data is typically processed offline, leading to significant delays in analysis, and it inherently suffers from a low SNR [3]. Furthermore, the complexity of its acquisition and processing steps can be a barrier for non-experts attempting to make clinical diagnoses [3].

To overcome the limitation of delayed feedback, rt-fMRI was introduced. Rt-fMRI integrates advanced data analysis and statistical capabilities (such as t-tests, the general linear model (GLM), and independent component analysis) directly into the acquisition pipeline, enabling online data processing [3]. This significantly shortens the preoperative examination process for patients. During surgery, it provides surgeons with real-time visualization of brain functional areas, allowing for the monitoring of the impact of surgical procedures on surrounding tissue.

Crucially, rt-fMRI offers real-time functional localization, which is vital for addressing brain shift (the displacement of brain tissue during an operation). While these capabilities offer immense advantages, this method is limited for tasks involving patients with motor impairments like hemiplegia, as their inability to execute specific movements prevents the mapping of corresponding motor areas [3]. Nevertheless, it remains a valuable direction for development.

Furthermore, rt-fMRI is a powerful tool for neurofeedback training. Through rt-fMRI neurofeedback, the behavioral effects of locally self-regulated brain activity can be studied, which in turn enables its application in fields such as the treatment of Parkinson's disease, the study of happiness-related parameters, and the interaction between automatic and controlled processes. Ultimately, it provides a powerful method for probing the causal links between brain activity and behavior, as well as exploring brain plasticity. [3-6]

To reduce data processing time, denoising in rt-fMRI has fewer steps than in conventional offline MRI, which could potentially lead to less effective noise removal. However, this is often compensated for by advanced algorithms. Even with sophisticated algorithms, rt-fMRI places high demands on subjects, as the slightest head shaking can cause artifacts, including image ghosting. Therefore, customized head fixation equipment is often used to reduce patient shaking. Additionally, rt-fMRI allows for the dynamic optimization of scanning parameters (such as k-space trajectory adjustments) to compensate for motion and improve image quality [3]. This principle is further advanced by integrating deep learning algorithms, which build neural network models from massive clinical data to predict a patient's motion trajectory accurately [10]. Beyond these computational corrections, shortening the time required for a single acquisition can reduce the displacement size of head shaking, thereby mitigating its impact.

The integration of artificial intelligence with MRI

Professionals operating MRI (such as MRI technicians and radiologists) must undergo considerable professional training to analyze and interpret MRI images correctly. This results in a shortage of MRI professionals in certain areas, especially where dual-reading systems are employed or medical resources are scarce. In addition, with the growth of the population and the increase in the detection frequency of certain diseases (such as prostate cancer detection), it is imperative to find a low-cost and user-friendly MRI solution [7]. Integration of AI with MRI, enabling AI to process and analyze images, represents a promising approach. With the help of AI's deep learning and automatic segmentation technology, it can significantly improve image quality and diagnostic efficiency. At present, the average performance of AI has surpassed that of some radiologists in specific, repetitive tasks. However, it is still inferior to the consensus of expert radiologists working in MDT or dual reading used in population screening [7,8]. This highlights its potential as a powerful assistive tool rather than a replacement. As shown in Table 1, Suhad Al-Shoukry and Zalili Binti Musa collated representative work from the last 10 years related to the use of AI in integration with MRI for the diagnosis of neurological disorders. They focused on studies that used different AI models and methods and reported clear performance metrics. The finding shows that MRI, when integrated with certain AI models, demonstrated good accuracy in detection. While these models are not inherently infallible, their key advantage is their immunity to human-specific factors, such as fatigue. This inherent consistency makes them highly trustworthy, providing reliable assistance to clinicians in detection and decision-making [8].

TABLE 1. More in-depth examination of the review of the literature. [9]

Title	Year	Methods & models	Performance	Discussion of methodology and its implications
Diagnosing Alzheimer's disease using MRI with deep and hybrid learning	2022	ResNet-18, Alex Net	Accuracy: 99.8%, Precision: 99.99%, AUC: 99.94%	Both Alex Net and ResNet-18 are employed, with the former offering simplicity and the latter enabling deeper feature extraction, leading to high precision. The integration of these models enhances diagnostic performance, though evaluation across diverse datasets is necessary to further confirm the method's effectiveness.
Deep sequence modeling on MRI for Alzheimer's diagnosis	2021	CNN (ResNet-18), Temporal Convolutional Network (TCN)	Accuracy: 91.78%, Sensitivity: 91.56%, Specificity: 92%	Employs TCN to model MRI sequences. Nonetheless, its accuracy is suboptimal, suggesting a necessity for enhanced temporal feature extraction. The methodology exhibits potential but may be improved by the integration of multi-modal data.
Hybrid deep learning and traditional methods for early detection of Alzheimer's	2021	Alex Net + SVM, ResNet-50 + SVM	Accuracy: 94.8%, AUC: 99.7%	A hybrid methodology that integrates deep learning for feature extraction with support vector machines (SVM) for classification. This equilibrium illustrates how hybrid models improve predicted precision and resilience, particularly in medical imaging.
Alzheimer's disease stage prediction using CNN	2020	CNN	Accuracy: 90.91%, F1 Score: 89.07%	CNN attains moderate accuracy, indicating that additional tuning or ensemble methods may be necessary. Emphasizes the difficulty of class imbalance in illness stage classification.
Brain tumour detection in MRI scans with hybrid CNN models	2020	ResNet-50, DenseNet201, VGG16	Accuracy: 97.2%	Integrates several CNNs, demonstrating that model amalgamation can enhance MRI analysis. The methodology possesses applicability beyond cerebral neoplasms, rendering it versatile for additional medical diagnoses.
Alzheimer's diagnosis via deep feature extraction and traditional models	2019	Random Forest (RF), SVM, K-Nearest Neighbors (KNN)	SVM Accuracy: 95.08%, RF Accuracy: 88%, KNN Accuracy: 85.12%	The SVM surpassed other classifiers in managing extracted features, demonstrating that conventional classifiers may greatly benefit from the feature extraction capabilities of deep learning. The implications indicate a wider application of this hybrid methodology in diagnostics.
AI for dementia and mild cognitive impairment diagnosis	2017	Google Net, ResNet	Accuracy: 99.7% (with transfer learning)	Demonstrates the efficacy of transfer learning in improving diagnostic precision with little data. This approach is optimal for medical applications characterized by limited data, delivering near-perfect accuracy when utilizing pre-trained models.

In addition, AI can detect details that radiologists may have missed during diagnosis. It can also automatically generate relevant images and perform processing to reduce image noise and artifacts, thereby improving image quality [10]. This enhances work efficiency and creates positive interaction with MRI operators [8]. Moreover, MRI integrated with AI is easier to use than traditional MRI and can be used to train novices, helping them get started quickly [8]. However, when the AI algorithm is inaccurate, it may misclassify information and produce results that contradict human judgment, thus generating a negative interaction with the operator [8]. Currently, the operator needs to make judgments based on personal experience while critically evaluating the AI's output, rather than unquestioningly trusting it, as either approach can lead to misjudgments [8].

To promote the development of the integration of AI with MRI, the focus should be on two aspects. First, future work should explore the integration of multiple, diverse AI models (ensemble methods) for deep learning to improve instrument accuracy and operating efficiency. Lastly, enriching the database resources is crucial. This should not be limited solely to past medical data. In the future, when using MRI integrated with AI, the focus should be on promptly comparing and analyzing AI-generated data with the operator's data. This process includes modifying any unreasonable parts of the AI's output. Additionally, AI should be allowed to learn in real time to improve its database continuously. This approach will enable the AI to perform daily tasks with both high efficiency and perfect accuracy, leading to improved overall work efficiency.

Portable low-field MRI

Portable MRI, also known as bedside MRI, is a type of simplified, low-cost imaging modality. Compared to conventional high-field MRI, it is substantially smaller and more economical, weighing approximately $\frac{1}{10}$ as much, consuming $\frac{1}{35}$ the energy, and costing as little as $\frac{1}{20}$ the price. This portability allows it to be deployed almost anywhere in a facility for on-demand scanning and processing [11]. For instance, installing it in an ambulance could enable pre-hospital diagnosis and intervention for the patient's condition, saving critical time by providing vital patient information before hospital arrival and allowing for more targeted life-saving treatments [11]. At the same time, this provides an alternative examination method for patients in remote or rural areas, those without insurance, or unwilling to visit regular medical institutions, broadening the accessibility of medical imaging examinations and overcoming traditional spatial limitations [12]. Furthermore, the patient experience is significantly improved, especially for patients with mental illness. Some participants reported that portable MRI's open design and flexibility create a more comfortable and less intimidating examination experience compared to conventional scans, partly by enabling scans in more familiar or convenient environments (Figure 1) [12].

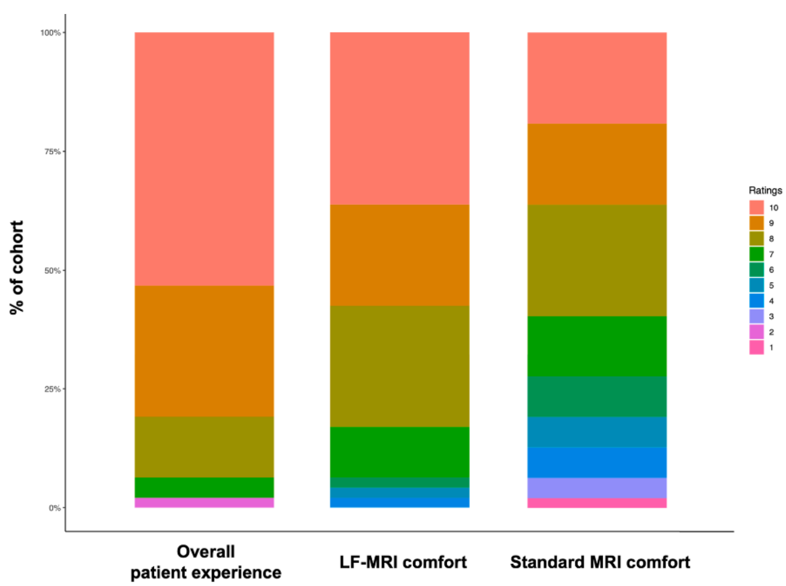

FIGURE 1. Participant experiences and comfort assessments for low-field and standard magnetic resonance imaging. Participants evaluated their overall experience with LF-MRI, comfort in the LF-MRI machine, and comfort in standard MRI machines using a 10-point Likert scale (1 signifying extremely low and 10 denoting very high). [12]

Note: Data for this study were collected from a cohort of adult multiple sclerosis (MS) patients who met the study criteria. This group included individuals aged 18 years and older with a confirmed diagnosis of MS and excluded subjects with contraindications to MRI, recent relapses, or active infections. [12]

The primary trade-off for the convenience of portable MRI is a significantly lower magnetic field strength. Some systems operate at fields as low as 0.064T, which inevitably reduces the resolution and quality of the image. However, this characteristic offers distinct advantages: reduced susceptibility to metallic artifacts. A compelling example is found in the work of Munhall et al., who studied the imaging of cochlear implants [13]. They compared scans from a portable 0.064T MRI with a conventional 3T MRI and identified a critical trade-off. Although the high-field 3T system provided superior overall image resolution, their analysis showed that the low-field 0.064T scanner generated markedly fewer artifacts and less image distortion around the metallic implant [13]. This reduction in artifacts is a key factor that lessens operators' concern about metallic objects, enabling the safe use of portable MRI in environments like emergency rooms, intensive care units, and mobile units like ambulances. Furthermore, it allows these systems to be used in conjunction with various medical instruments, facilitating rapid diagnosis at the point of care.

This diagnostic utility is further supported by other studies. For instance, in scans of progressive multifocal leukoencephalopathy (PML), a portable ultra-low-field MRI (pULF-MRI) was able to detect all T2-FLAIR lesions that were also identified by conventional high-field MRI [14]. This suggests that for certain pathologies, the accuracy of low-field MRI is not inferior to high-field systems, highlighting it as a promising direction for development.

Despite these advantages, portable low-field systems face two major challenges: low SNR and a high degree of $\mathbf{B_0}$ field inhomogeneity [15]. To address the above problems, several strategies are being explored. On the hardware level, solutions include modifying coil geometry (e.g., to an elliptical shape) and designing multi-layered shielding systems to reduce external electromagnetic interference (EMI) [15]. Concurrently, on the software and signal processing levels, approaches involve designing advanced digital filters and developing software algorithms to compensate for $\mathbf{B_0}$ inhomogeneity. These combined efforts aim to ensure magnetic field uniformity, thereby improving the imaging quality of low-field MRI.

CONCLUSION

The article first summarizes the basic principles of MRI from the perspectives of the magnetic resonance phenomenon and the MRI imaging process. The article then describes the four latest developments in MRI in chronological order. The first is high-field MRI. Under the action of a high magnetic field, the SNR of MRI signals is improved. This enhancement increases the resolution of the image generated, allowing for imaging at the sub-millimeter level. This advancement provides technical support for studying brain structure and related diseases. For example, detailed imaging data of the hippocampus can be used to evaluate the effectiveness of medications for treating Alzheimer's disease. Next is rt-fMRI, which conducts real-time cerebral activity imaging by identifying blood flow-related alterations. The detected neural feedback can provide neural activity data for neurological diseases such as Parkinson's, helping doctors conduct research and analysis. Then there is the integration of AI with MRI. AI can reduce the difficulty of users getting started and help MRI workers identify omissions, which can assist in lowering the misdiagnosis rate. In addition, AI's deep learning and automatic processing can improve image clarity by reducing noise and artifacts. Finally, the portable low-field MRI overcomes the space limitation due to its small size. Its portability provides a new means of examination for people in remote areas. They do not have to travel to large hospitals for relevant diagnoses. This feature broadens the application scope of MRI.

Despite their distinct advantage, these technologies also present a series of notable challenges. A primary concern is their susceptibility to interference and artifacts that degrade image quality. For instance, motion artifacts from even slight subject movements pose a significant challenge for rt-fMRI, while high-field systems are prone to magnetic susceptibility artifacts that distort images around metallic implants. Beyond artifacts, performance is constrained by other technical hurdles. Magnetic field inhomogeneity remains a persistent issue for both high-field and portable low-field MRI. Concurrently, a low SNR fundamentally limits the image quality of rt-fMRI and portable systems. Finally, a critical safety concern, especially for high-field MRI, is the potential for RF-induced tissue heating, which is quantified by the SAR. While perfect solutions are not yet available, concerted efforts are focused on mitigating these impacts through innovations in both hardware and software.

For the future, two suggestions can be made. The first approach is algorithmic. The foundation of this approach is the establishment of a shared medical imaging database. This database enables the development of AI-integrated algorithms for real-time motion tracking compensation. It also supports artifact elimination and image reconstruction algorithms. These algorithms can then be optimized for specific clinical applications to enhance their anti-interference capabilities. Lastly, the development of acquisition technology should focus on rapid acquisition techniques to reduce scan time and minimize susceptibility to external influences.

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