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Review on the Development and Application of Compressed Sensing in MRI for Disease Diagnosis

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ABSTRACT
Magnetic Resonance Imaging (MRI) plays an irreplaceable role in clinical diagnosis due to its superior soft tissue contrast and a wide range of imaging parameters. However, its clinical efficiency is limited by prolonged scan times and sensitivity to motion artifacts. This study focuses on the clinical application of Compressive Sensing (CS) in MRI, employing a combination of systematic literature review and practical case analysis to comprehensively explore its recent developments and applications. The findings indicate that CS, based on the principles of sparsity and incoherent sampling, can achieve high-quality image reconstruction under undersampling conditions, significantly improving imaging efficiency. Nevertheless, challenges remain, including artifact issues at high acceleration rates, the need for algorithm optimization, and computational complexity. With the integration of emerging technologies such as Artificial Intelligence and multi-center clinical validation, CS technology holds promise for broader adoption and standardization in the MRI field, providing strong support for precision medicine and personalized treatment.

KEYWORDS
Magnetic Resonance Imaging (MRI); Compressive Sensing (CS); Imaging Acceleration; Clinical Applications; Algorithm Optimization

1 Introduction

Magnetic Resonance Imaging (MRI) has become a cornerstone of modern medical diagnostics, providing exceptional soft tissue contrast without ionizing radiation. Its high sensitivity to soft tissues and versatile imaging contrast parameters allow for detailed visualization of anatomical structures, physiological functions, and metabolic activities [1][2]. However, the slow imaging speed of MRI, due to point-by-point k-space data acquisition, remains a challenge. Despite advancements in fast imaging techniques like FLASH, Fast Spin Echo (FSE), and Echo Planar Imaging (EPI), imaging speed improvements still fall short when high resolution or dynamic imaging is required [3]. Parallel imaging (PI) has accelerated MRI, but image quality typically degrades when the acceleration factor exceeds 2 [4].

Compressed Sensing (CS) has revolutionized MRI by enabling high-quality image reconstruction from fewer k-space samples, significantly reducing scan time. Using nonlinear optimization algorithms to maintain data consistency and sparsity, CS fills in unsampled data during reconstruction [5]. Since its introduction by Lustig et al., CS has shown substantial acceleration potential in clinical applications, including cardiovascular, abdominal, and brain imaging, and has received FDA approval for various clinical scans [2]. This technology has not only enhanced imaging speed but also ushered in the era of fast MRI.

This review aims to systematically analyze the latest developments in CS technology for MRI, focusing on its clinical applications. While current reviews often lack practical case studies and in-depth discussions on diagnostic efficacy, this paper incorporates real clinical cases to highlight CS's effectiveness in diagnosing diseases and to guide future research and clinical practice.

2 Technical Aspects and Progress

2.1 Data Acquisition Strategies

MRI data acquisition strategies can be classified into random sampling, Nyquist sampling, and non-Cartesian sampling methods. Random sampling, introduced by Compressed Sensing (CS) theory, reduces the number of sampling points by skipping phase encoding lines in k-space, minimizing artifacts and accelerating image reconstruction while maintaining reliability [3][5]. The Nyquist sampling theorem requires a sampling rate at least twice the signal bandwidth to avoid aliasing artifacts, but this increases scan times and hardware demands [1][5].

CS techniques address this by reducing the sampling rate and leveraging sparsity and incoherence principles to enable high-quality reconstruction even at sub-Nyquist rates [3][5]. Non-Cartesian methods, such as radial and spiral sampling, enhance spatial coverage and reduce motion artifacts by collecting data along spoke-like or spiral trajectories, improving acquisition efficiency and reconstruction accuracy [1][5][6].

2.2 Artifacts and Signal-to-Noise Ratio (SNR) Challenges

In Compressed Sensing (CS) MRI, increasing the acceleration factor often leads to challenges such as image artifacts and reduced signal-to-noise ratio (SNR). Jaspan et al. (2015) [4] found that acceleration factors exceeding 2x can cause artifacts like "global ringing" and detail blurring, hindering lesion identification and reducing diagnostic accuracy. Additionally, as the sampling rate decreases, SNR drops, negatively affecting image quality and diagnostic utility. While CS techniques leverage sparsity and regularization to mitigate these issues, they may introduce noise suppression and image smoothing, compromising fine details, particularly in detecting lesion boundaries. As acceleration rates increase, SNR degradation becomes more pronounced, and although enhancing the regularization parameter can improve SNR, it may result in a loss of image details, reducing consistency with the original data [4].

2.3 Integration with Parallel Imaging Techniques (e.g., SENSE and GRAPPA)

The introduction of parallel imaging techniques, such as SENSE (Sensitivity Encoding) and GRAPPA (Generalized Autocalibrating Partially Parallel Acquisitions), has significantly accelerated MRI data acquisition and facilitated the clinical application of compressed sensing (CS). SENSE, which reduces acquisition time by utilizing the spatial sensitivity map of receiving coils to resolve aliasing artifacts, shifts part of the sampling task from the magnetic field gradients to coil sensitivities [2][5]. In contrast, GRAPPA operates in k-space, reconstructing images by interpolating missing samples through self-calibration without requiring explicit sensitivity maps, and is particularly effective at handling motion artifacts and complex sampling trajectories [5][7]. Dieckmeyer et al. (2021) examined the combined effect of CS and parallel imaging on brain volume measurements, finding that while higher CS acceleration factors increased noise and caused systemic bias, measurement reliability remained high for lower to moderate acceleration factors (e.g., CS factors < 12), suggesting these techniques can effectively balance imaging speed with accuracy [7].

3 Clinical Applications and Disease Diagnosis

3.1 Neurological Disorders

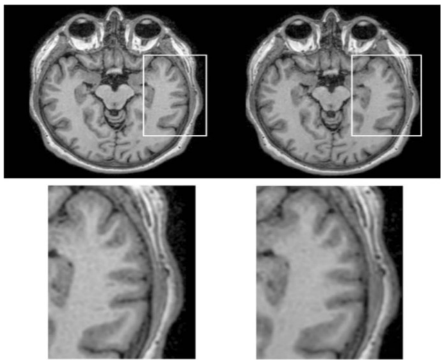

Figure 1[8] Brain 3D T1 Gd (transverse): CS sequence (right) has less noise, but the white-gray matter transition is slightly blurrier compared to the conventional (left)

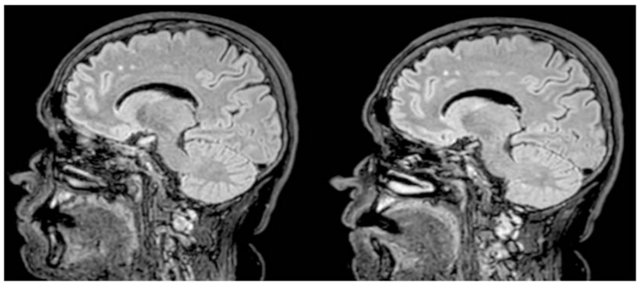

Figure 2[8] Brain 3D FLAIR sequence: CS (right) has less noise globally but shows less detail in small structures (e.g., cerebellum)

White matter lesions in the frontal lobe are visible on both sequences. Compressed Sensing (CS) technology has improved the diagnosis of neurological disorders, including brain tumors, multiple sclerosis (MS), and stroke. Mönch et al. (2019) showed that CS reduced 3D FLAIR scan time by 29.3%, enhancing resolution and reducing motion artifacts [9]. Jaeger et al. (2020) found that CS with 4D flow MRI cut scan time by 40% while maintaining accuracy in cerebrospinal fluid dynamics [10]. In MS, CS-accelerated 3D-T1 imaging improved brain volume analysis, reduced scan time, and minimized motion artifacts, ideal for monitoring lesions [7]. CS with noise suppression and deep learning may further enhance lesion detection. Boudabbous et al. (2019) showed that CS-optimized MRI improves clinical efficiency by reducing scan time without sacrificing diagnostic quality [8]. In stroke, CS-optimized T2* sequences improved detection of small hemorrhages and infarcts, aiding early intervention, while CS with DCE-MRI and ASL enabled real-time cerebral hemodynamic monitoring [9][11].

Spinal cord imaging is essential for diagnosing neurological disorders, and Compressed Sensing (CS) has enhanced its efficiency and accuracy. Jaeger et al. (2020) showed that CS-accelerated 4D flow MRI reduced scan time by 40% while maintaining accuracy in cerebrospinal fluid (CSF) dynamics, with acceleration factors between 4 and 6 showing no significant loss in imaging quality [10]. Fervers et al. (2023) combined CS with deep learning to improve lumbar imaging, preserving structural details and enhancing the contrast-to-noise ratio, aiding in diagnosing lesions like spinal cord compression and radiculopathy [12]. However, higher acceleration factors above 8 increase noise and artifacts, highlighting the need for further optimization of reconstruction algorithms to balance speed and quality.

3.2 Cardiovascular System Diseases

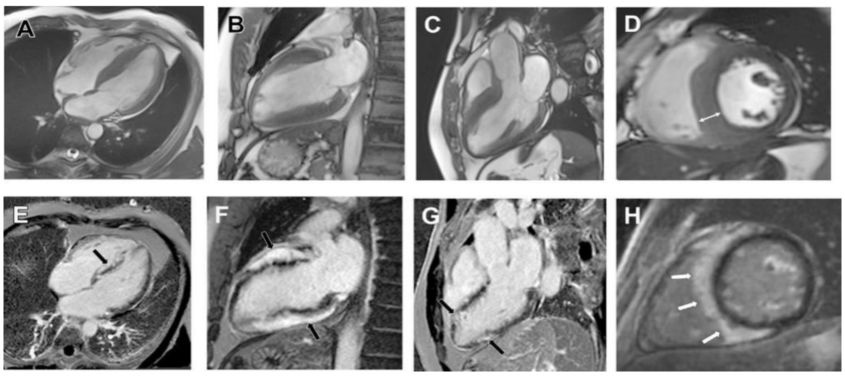

Figure 3[11] MRI of the heart in a 43-year-old man presenting with syncope, with no other significant medical history

Wang et al. (2020) evaluated Compressed Sensing (CS) for cardiac function assessment under single breath-hold conditions in 154 patients with suspected heart failure, finding that CS reduced scan time by 12% while maintaining excellent consistency in left ventricular ejection fraction (LVEF) and end-diastolic volume (LVEDV) (kappa=0.934, $p<0.05$) [13]. An et al. (2023) showed that CS-MRI outperformed traditional methods in sensitivity and specificity, achieving over 90% for PFR2 and FV2, and improving peak signal-to-noise ratio (PSNR) and structural similarity (SSIM), supporting precise heart failure classification [14]. Delattre et al. (2019) demonstrated that CS reduces scan time by 30%-60% and minimizes motion artifacts, enhancing comfort during long-duration scans of heart failure patients [8].

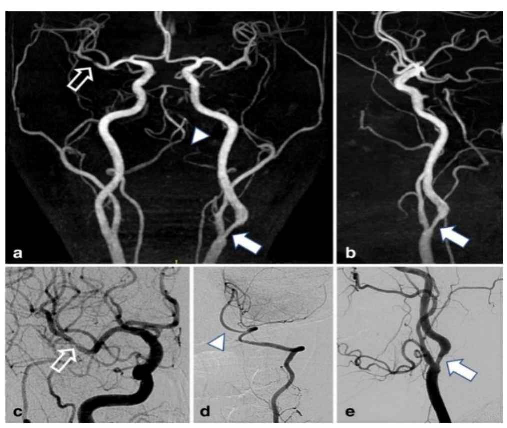

Figure 4[6] CS TOF-MRA and DSA in a 53-year-old patient for vascular imaging

Yamamoto et al. (2018) applied Compressed Sensing (CS) in time-of-flight MRA (TOF-MRA) for Moyamoya disease, reducing scan time by two-thirds while maintaining high consistency with traditional methods and improving visualization of small vessels in the basal ganglia ($p < 0.0001$). At R=5, scan time was reduced to 2 minutes and 42 seconds, demonstrating CS's efficiency for diagnosing cerebrovascular diseases [15]. Pathrose et al. (2020) showed that CS-MRA reduced scan times to under 3 minutes at R=7.7 and 10.2, though it underestimated peak velocity and wall shear stress by 9%-14%, requiring accuracy adjustments [16]. Matcuk et al. (2020) found that CS allowed up to 12-fold acceleration in MRA while preserving image quality, offering significant benefits for rapid emergency diagnosis [11].

3.3 Diseases in other parts of the body

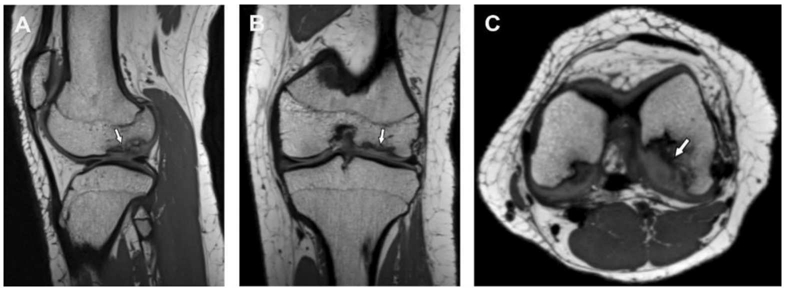

Figure 5[11] A 13-year-old boy experiencing pain in the right knee

Ni et al. (2023) demonstrated that AI-assisted compressed sensing (ACS) in 3D-MRI of the knee joint reduced scan time to 160 seconds with 10-fold acceleration, maintaining diagnostic consistency with 2D-MRI (κ=0.81−0.94) and optimizing post-processing workflows [17]. Dratsch et al. (2023) showed that CS combined with deep learning (CS-AI) in shoulder joint imaging reduced scan time by 40% and 38% at 4-fold and 13-fold acceleration, respectively, without compromising diagnostic accuracy [18]. Matcuk et al. (2020) found that CS reduced knee joint cartilage lesion scan time by over 50% while preserving image quality, outperforming traditional parallel imaging in 3D imaging and fine structure visualization [11][19]. Zhao et al. (2022) applied ACS in renal MRI, completing T2-weighted imaging in 17 seconds, improving signal-to-noise ratio (SNR) (3.63±0.76 vs. 3.04±0.44) and contrast-to-noise ratio (CNR) (14.44±4.53 vs. 12.05±3.32, $p<0.001$), offering an efficient solution for renal imaging [20]. Ueda et al. (2021) combined CS with deep learning for pelvic imaging, significantly reducing T2-weighted imaging time, improving SNR, and enhancing soft tissue contrast for complex lesions like uterine fibroids and ovarian cysts [21].

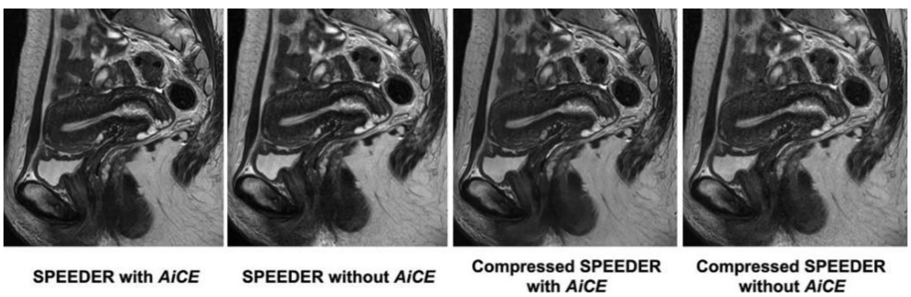

Figure 6[21] A 43-year-old woman diagnosed with a Nabothian cyst

Sun et al. (2021) applied compressed sensing (CS) in liver dynamic contrast-enhanced MRI, demonstrating that CS-T1 sequences improved liver-lesion contrast and reduced motion artifacts compared to traditional parallel imaging, aiding early liver cancer diagnosis [22]. The study aims to optimize CS sampling patterns for dynamic imaging across multiple respiratory cycles.

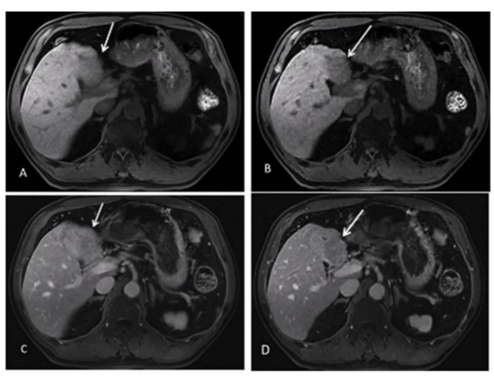

Figure 7[22] A 65-year-old man diagnosed with hepatocellular carcinoma at the junction of the left and right liver lobes

Accurate imaging of small intestine diseases is crucial for diagnosing inflammatory bowel diseases (IBD), with magnetic resonance enterography (MRE) widely used. Compressed sensing (CS) accelerates scan speed and reduces artifacts in MRE [8][23]. Kim et al. (2022) found that CS-enhanced SENSE (CS-SENSE) reduced scan time from 17.2 to 11.5 seconds ($p < 0.001$), improved image quality ($p = 0.02$), and reduced motion artifacts ($p = 0.006$), while enhancing sensitivity (86%-92%) and accuracy (87%-91%) in diagnosing active inflammation, particularly in the terminal ileum and ascending colon [23]. Boudabbous et al. (2019) showed that CS reduced scan time by 30%-60% in multi-organ 3D imaging and improved the detection of active inflammation and features like bowel wall thickening and ulcers [8].

4 Conclusion

This paper researched the development and clinical application of Compressed Sensing (CS) technology in Magnetic Resonance Imaging (MRI), focusing on its ability to accelerate scan times while maintaining high image quality. The study discusses the principles of CS, such as sparsity and incoherent sampling, and how these principles allow for efficient image reconstruction with fewer data points. Various applications of CS in diagnosing neurological disorders, cardiovascular diseases, and musculoskeletal conditions are reviewed, demonstrating that CS improves scan efficiency and reduces motion artifacts, making it particularly valuable for dynamic and high-resolution imaging.

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