

Joint Coil Sensitivity Estimation and Image Reconstruction for Accelerated Magnetic Resonance Imaging

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Abstract:

Parallel imaging techniques accelerate magnetic resonance imaging by leveraging spatial sensitivity variations of multi-channel coils. The accuracy of coil sensitivity estimation directly impacts the fidelity of reconstructed images. Traditional methods often rely on auto-calibration signals or independent sensitivity estimation, which are prone to high-frequency information loss, error propagation, and sensitivity to calibration data quality. This paper systematically reviews joint optimization methods for coil sensitivity estimation and image reconstruction, with a focus on deep learning-based end-to-end joint reconstruction networks. We analyze their theoretical foundations, model architectures, and performance. Studies demonstrate that joint reconstruction methods effectively suppress error propagation through synergistic optimization, maintaining high reconstruction quality and robustness even under high acceleration factors and limited or absent ACS. Deep learning-driven strategies enhance the recovery of high-frequency details and improve overall image quality, providing critical theoretical and practical support for advancing fast MRI technologies.

Keywords:

Parallel Imaging, Coil Sensitivity, Deep Learning

1. Introduction

Parallel imaging (PI) accelerates magnetic resonance imaging (MRI) by leveraging spatially varying sensitivity profiles of multi-channel receiver coil arrays to enable k-space undersampling [1]. The accuracy of the estimated coil sensitivity maps is critical, as it fundamentally limits the fidelity of the final reconstructed image. Conventional estimation strategies, primarily dependent on auto-calibration signal (ACS) data, face inherent limitations in practice. SENSE [1] and GRAPPA [2] /ESPIRiT [3] algorithms are prone to error propagation and loss of high-frequency image components, particularly at high acceleration factors or with insufficient calibration data. While calibration-free methods utilizing inherent data characteristics offer a viable alternative, they often involve excessive computational demands and sensitivity to

parameter tuning, which constrain their clinical utility. A fundamental weakness of these traditional approaches lies in their sequential estimation framework, wherein errors in initial sensitivity maps are irrevocably coupled into the subsequent image reconstruction process, frequently manifesting as residual aliasing or noise amplification [4].

To address these limitations, joint reconstruction frameworks have been developed to simultaneously estimate the image and coil sensitivity maps within a unified inverse problem. Early model-based iterative methods established the theoretical foundation for this co-optimization, demonstrating that synergistically solving for both unknowns could mitigate error propagation [4]. However, these approaches often remained computationally intensive and relied on hand-crafted regularizers, which limited their practical utility. The advent of deep learning has since transformed this paradigm, introducing data-driven models capable of end-to-end reconstruction directly from undersampled data. These networks learn powerful priors from large datasets, enabling robust performance under high acceleration and markedly improving the recovery of anatomical detail, even in the absence of explicit auto-calibration signals [5].

This review synthesizes advances in joint reconstruction for coil sensitivity and image estimation in parallel MRI, contrasting optimization-based and deep learning methods. Key challenges in generalizability and interpretability are addressed, with self-supervised learning and physics-informed architectures emerging as critical pathways toward robust, high-speed clinical MRI.

2. Parallel Imaging and Sensitivity Estimation

2.1. Parallel Imaging Model

Parallel imaging is a widely adopted technique for accelerating MRI data acquisition by leveraging the spatial sensitivity variations of an array of receiver coils. The fundamental forward model for multi-coil MRI acquisition can be formulated as an inverse problem. The goal is to reconstruct a desired image, $\mathbf{x} \in \mathbb{C}^N$, from the undersampled k-space measurements, $\mathbf{y} \in \mathbb{C}^{JN \times 1}$, acquired by J coils.

The undersampling process is mathematically represented by an operator $\mathbf{u}$, which masks the fully sampled k-space according to a predefined pattern. The acquired data from all coils can be expressed collectively as

$$\mathbf{y} = \mathbf{UFSx} \quad (1)$$

Here, $\mathbf{F}$ denotes the Fourier transform operator, $\mathbf{S} = [\mathbf{S}_1; \dots; \mathbf{S}_J; \dots; \mathbf{S}_J] \in \mathbb{C}^{JN \times N}$ represents the concatenated coil sensitivity matrices.

The core principle of PI is to use the distinct spatial information encoded by $\mathbf{S}$ to compensate for the reduced k-space sampling, thereby breaking the Nyquist limit and enabling significant scan time reduction. The reconstruction problem is inherently ill-posed, and its effectiveness critically depends on the accuracy of the coil sensitivity matrix $\mathbf{S}$. Inaccurate estimation of $\mathbf{S}$ can lead to significant artifacts, noise amplification, and loss of anatomical details in the reconstructed image, particularly at high acceleration factors.

2.2. Sensitivity Estimation Methods and Their Limitations

Traditional sensitivity estimation methods are predominantly categorized into two groups: those dependent on ACS and calibration-free (calibrationless) techniques.

ACS-based methods utilize a fully sampled central k-space region to derive coil sensitivity information. In image-domain approaches such as SENSE, sensitivity maps are commonly obtained by dividing individual coil images from the ACS by a composite reference image, typically generated using the sum-of-squares method. These maps inherently assume smooth spatial variation of coil sensitivities, an assumption that frequently breaks down at high acceleration factors or near field-of-view boundaries, resulting in significant noise amplification and structured aliasing artifacts. K-space methods, including GRAPPA and ESPIRiT, employ the ACS region to learn interpolation kernels or compute sensitivity maps through eigenvalue decomposition. While effective in standard scenarios, these methods demonstrate critical vulnerability when ACS data is limited, as the resulting inaccuracies in sensitivity estimation directly propagate to the final reconstruction, causing substantial image degradation and loss of anatomical detail.

Calibrationless methods have emerged to overcome the inherent limitations of ACS-dependent approaches, particularly the extended acquisition time and increased motion sensitivity associated with ACS acquisition. These techniques exploit the structured low-rank properties of multi-coil k-space data, with representative algorithms including SAKE [6] and LORAKS [7]. By formulating the reconstruction problem as a structured matrix completion task, these methods implicitly model coil correlations without explicit sensitivity map estimation. However, their practical adoption faces significant challenges, primarily due to the substantial computational overhead involved in constructing and decomposing large-scale matrices. Furthermore, the strict low-rank assumption may not fully capture the complex relationships in experimental data, potentially limiting reconstruction quality in challenging imaging scenarios.

The fundamental limitation unifying these traditional approaches lies in their sequential estimation framework. Both ACS-based and calibrationless methods typically perform sensitivity estimation and image reconstruction as separate, disconnected processes. This decoupled approach creates a critical point of failure: any inaccuracy in the initial sensitivity estimation, particularly the loss of high-frequency components, becomes irreversibly embedded in the final reconstructed image. This error propagation mechanism represents the primary motivation for developing joint reconstruction frameworks that simultaneously optimize both sensitivity maps and image content within a unified, coherent computational framework.

3. Joint Reconstruction Methods: From Traditional to Deep Learning

3.1. Traditional Joint Reconstruction Methods

Traditional joint reconstruction methods are founded on the core principle of formulating the estimation of both the target image and the coil sensitivity maps as a coupled optimization problem. This integrated approach aims to mitigate the error propagation inherent in sequential estimation strategies. The general mathematical framework is typically expressed as a cost minimization problem that incorporates

data fidelity terms for both the image and the sensitivities, along with explicit regularization terms:

$$\min_{\mathbf{x}, \mathbf{S}} \frac{1}{2} \|\mathbf{y} - \mathcal{UFS}\mathbf{x}\|_2^2 + \mathcal{R}_1(\mathbf{x}) + \mathcal{R}_2(\mathbf{S}) \quad (2)$$

Here, $\mathcal{R}_1(\mathbf{x})$ and $\mathcal{R}_2(\mathbf{S})$ represent the regularization terms imposed on the image and the sensitivity maps, respectively. A standard algorithm for solving this problem involves an alternating minimization scheme, which iteratively updates one variable while keeping the other fixed.

With the sensitivity maps $\mathbf{S}$ fixed, the image $\mathbf{x}$ is updated by solving:

$$\mathbf{x}^{(k)} = \arg \min_{\mathbf{x}} \frac{1}{2} \|\mathcal{UFS}^{(k-1)}\mathbf{x} - \mathbf{y}\|_2^2 + \mathcal{R}_1(\mathbf{x}) \quad (3)$$

Subsequently, with the image $\mathbf{x}$ fixed, the sensitivity maps $\mathbf{S}$ are updated by solving:

The regularization for the sensitivity maps, $\mathcal{R}_2(\mathbf{S})$, often leverages their physical characteristics, primarily their spatial smoothness. A common approach is to model the sensitivity profiles using polynomial functions or to enforce smoothness through Gaussian filtering. This serves to reduce the number of free parameters and stabilizes the inversion process.

A seminal work in this category is JSENSE, which explicitly incorporates this alternating optimization paradigm. While these traditional joint methods establish a crucial theoretical foundation by demonstrating the benefits of synergistic estimation, they possess notable limitations. The reconstruction process is often computationally intensive and time-consuming due to the iterative optimization algorithm. Furthermore, the performance is highly dependent on the careful manual selection of regularization constraints and their associated parameters, which can be non-trivial. Despite these practical challenges, the core concept of jointly optimizing the image and sensitivity maps provides a critical theoretical blueprint that is later adopted and enhanced within deep learning-based frameworks.

3.2. Deep Learning-Driven Joint Reconstruction Methods

Deep learning has fundamentally transformed the paradigm for joint reconstruction in parallel MRI by introducing data-driven, end-to-end learning frameworks [5,8,9,10]. These methods leverage the powerful nonlinear mapping capabilities of deep neural networks to directly learn the synergistic estimation of coil sensitivity maps and the target image from undersampled multi-coil k-space data, thereby circumventing the explicit modeling and manual parameter tuning required in traditional iterative approaches.

A prominent strategy involves unrolled networks that mimic the iterative process of conventional algorithms but replace hand-crafted regularizers with learnable convolutional modules. The JDSI [10] network exemplifies this approach by designing a recursive architecture with dedicated modules for sensitivity estimation and image reconstruction, which alternate to mutually refine each other. Crucially, it estimates sensitivity maps from the entire acquired k-space data rather than being confined to the ACS region, enabling the recovery of high-frequency information and leading to more faithful sensitivity estimates. This joint optimization process,

visualized through intermediate network outputs, demonstrates a clear mutual promotion: as image artifacts are progressively removed, the sensitivity maps become more accurate, which in turn facilitates higher-quality image reconstruction. This design provides enhanced interpretability compared to purely black-box models. Figure 1 compares the sensitivity maps estimated by an end-to-end network using different undersampling patterns as input. (Figure 1)

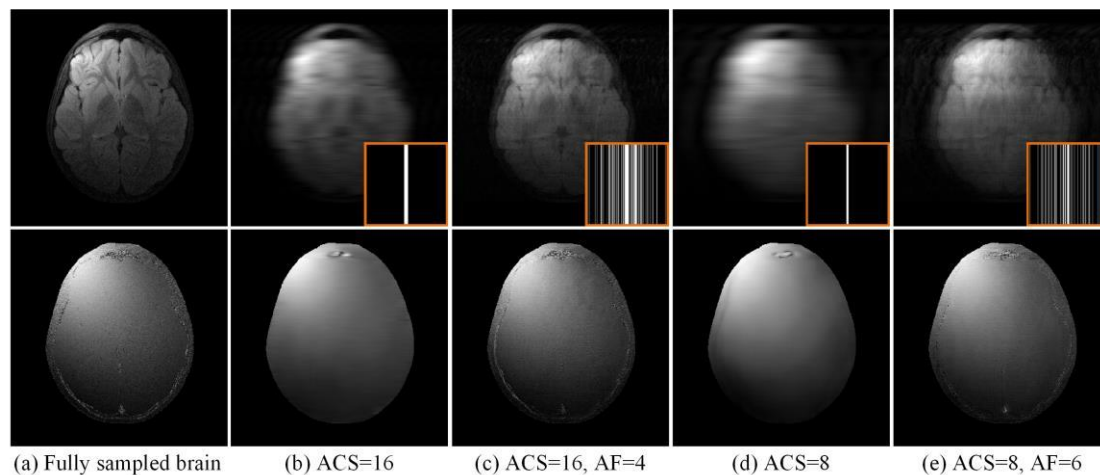


Figure 1. Comparison of sensitivity estimated by end-to-end network with different data inputs. (b) and (d) show the undersampled images and the corresponding estimated sensitivity using only central k -space data. (c) and (e) show the undersampled images and the corresponding estimated sensitivity using Cartesian random sampling. AF denotes the acceleration factor.

Another innovative approach moves beyond explicit sensitivity map estimation by employing implicit neural representations (INR). The IMJENSE [11] framework models the underlying MRI image as a continuous function of spatial coordinates, parameterized by a sinusoidal representation network. Simultaneously, it represents coil sensitivity maps using smooth polynomial functions. The weights of the network and the coefficients of the polynomials are jointly optimized directly from the sparsely sampled k -space measurements without any fully sampled training data. This scan-specific, training-database-free method inherently incorporates a continuity prior and, by jointly solving for both entities, prevents error propagation from imperfect pre-estimated sensitivities. Its performance remains robust even with an extremely small number of ACS lines, showcasing significant potential for high acceleration.

These deep learning-driven methods offer substantial advantages, including superior reconstruction quality with enhanced detail preservation, robustness to high acceleration factors and limited ACS, and fast inference times suitable for clinical deployment. However, challenges remain, such as the need for large, diverse training datasets for supervised methods, potential generalization issues across different scanners or anatomies, and the computational demands of scan-specific approaches like INR. Despite these challenges, the integration of deep learning with physical forward models establishes a powerful and flexible foundation for the next generation of fast, high-fidelity MRI reconstruction[12].

3.3. Calibrationless Joint Reconstruction

Calibrationless joint reconstruction represents a pivotal advancement in parallel MRI, aiming to completely eliminate the dependency on specially acquired ACS data. This paradigm maximizes acquisition efficiency by avoiding the time overhead

and potential motion sensitivity associated with ACS collection, while simultaneously addressing the challenge of accurately estimating coil sensitivity profiles from highly undersampled data.

Traditional calibrationless methods, such as SAKE and LORAKS, exploit the inherent structured low-rankness of the multi-coil k-space data. These techniques construct a block-Hankel matrix from the undersampled measurements and enforce a low-rank constraint as a joint prior, implicitly modeling both the image content and coil correlations without explicit sensitivity map estimation. While theoretically able to operate without ACS, these methods are often hampered by high computational complexity due to large-scale matrix constructions and decompositions, and their performance can be sensitive to the selection of regularization parameters.

Deep learning has profoundly reshaped the calibrationless landscape by providing powerful data-driven priors. Learning-based approaches can be categorized into implicit and explicit sensitivity modeling strategies. Implicit methods, such as certain unrolled networks [13,14], do not output sensitivity maps directly but instead employ convolutional layers to inherently learn and exploit spatial correlations between coils throughout the reconstruction process. Explicit methods, conversely, directly estimate sensitivity maps from the undersampled data. The JDSI network, for instance, can function in a calibrationless mode by leveraging its sensitivity estimation module over all acquired k-space points, enabling high-frequency detail recovery. The IMJENSE framework offers a unique scan-specific solution by jointly learning a continuous implicit neural representation for the image and a polynomial model for the sensitivities directly from the undersampled k-space, requiring no pre-training on a fully sampled database.

The principal challenge in calibrationless reconstruction lies in the severe ill-posedness of the problem [9]. Deep learning methods address this by leveraging powerful data-driven priors learned from large datasets, using network architectures that inherently encode properties like spatial smoothness for sensitivities, and employing self-supervised or scan-specific learning techniques that do not require fully sampled ground truth data. These approaches demonstrate that accurate joint estimation of both the image and coil sensitivities is feasible even in the absence of ACS, pushing the boundaries of achievable acceleration in clinical MRI.

4. Advantages and Challenges

4.1. Technical Advantages

The integration of deep learning into joint reconstruction frameworks yields substantial technical improvements over conventional sequential approaches. These advantages manifest primarily in three domains: enhanced reconstruction fidelity, improved robustness under accelerated sampling, and clinically viable computational efficiency.

A key advantage lies in the superior preservation of anatomical details and structural integrity. Unlike traditional methods where inaccuracies in pre-estimated sensitivity maps propagate irreversibly into the final reconstruction, joint frameworks progressively refine both sensitivity estimates and image content. The JDSI network demonstrates this capability through its alternating optimization architecture, where each iteration simultaneously enhances sensitivity map accuracy

and reduces image artifacts. This cooperative process recovers high-frequency information often lost in conventional processing, producing images with sharper tissue boundaries and improved lesion conspicuity. The IMJENSE approach further advances this paradigm through its continuous representation of both image and sensitivity functions, effectively enforcing physical constraints while maintaining fine anatomical textures.

These methods also exhibit exceptional resilience to challenging acquisition conditions. Traditional techniques frequently fail when auto-calibration signals are limited or acceleration factors exceed conventional limits. Deep learning-based joint reconstruction addresses this fundamental limitation through several mechanisms: JDSI utilizes the entire acquired k-space for sensitivity estimation rather than relying solely on ACS regions, while IMJENSE's scan-specific optimization directly learns from available measurements without external training data. This enables robust performance even at acceleration factors of 6-8 with minimal calibration signals, significantly expanding the practical boundaries of rapid MRI.

From a practical standpoint, these approaches offer compelling computational advantages once trained. While traditional joint methods require computationally intensive iterative optimization, deep learning implementations perform reconstruction through efficient network inferences. The JDSI network achieves high-quality reconstructions through a fixed number of unrolled iterations, and IMJENSE's coordinate network representation enables rapid image synthesis after optimization. This efficiency translates to reconstruction times compatible with clinical workflow requirements, making high-quality accelerated imaging practical for routine application. Together, these technical advantages establish deep learning-powered joint reconstruction as a foundation for the next generation of fast, high-fidelity magnetic resonance imaging.

4.2. Challenges

Despite their promising performance, deep learning-based joint reconstruction methods face several critical challenges that must be addressed before widespread clinical adoption can be realized.

A primary concern is the limited generalization capability of supervised models. Networks like JDSI, trained on specific datasets from particular scanner platforms and coil configurations, often experience significant performance degradation when applied to data from different vendors, field strengths, or anatomical regions. This distribution shift problem stems from the fundamental difference between learning the underlying physics of MRI and merely memorizing data-specific features present in the training set. The issue becomes particularly pronounced in clinical settings where scanner heterogeneity is the norm rather than the exception.

The data dependency of these methods presents another substantial barrier. Supervised approaches require large datasets of fully-sampled, high-quality ground truth images for training, which are expensive to acquire and often unavailable for certain clinical applications or emerging imaging contrasts. Furthermore, the curation of these datasets raises concerns regarding patient privacy and data sharing across institutions. Even self-supervised and scan-specific methods like IMJENSE face computational burdens, as their requirement for per-scan

optimization leads to extended reconstruction times that may not align with clinical workflow demands.

The interpretability deficit in deep learning models remains a significant obstacle to clinical trust. While traditional algorithms operate on well-established physical principles with transparent error sources, the decision-making process of deep networks often functions as a “black box.” This opacity makes it difficult to identify failure modes or understand the underlying reasons for specific reconstruction outcomes. The problem is particularly acute in medical imaging, where diagnostic decisions carry profound clinical implications and require explainable reasoning.

Additionally, the pathological fidelity of reconstructed images warrants careful investigation. Networks predominantly trained on data from healthy volunteers may inadvertently suppress or alter subtle pathological findings that deviate from learned patterns of normal anatomy. This risk of introducing false features or suppressing true abnormalities represents a serious concern that must be thoroughly evaluated through rigorous clinical validation studies. The absence of standardized evaluation metrics that correlate strongly with diagnostic value further complicates the assessment of clinical utility, as conventional quantitative metrics like PSNR and SSIM do not necessarily reflect diagnostic accuracy.

4.3. Future

Future developments in joint reconstruction will likely focus on enhancing methodological robustness and clinical applicability. Key directions include advancing self-supervised learning techniques to alleviate dependency on fully-sampled data, and developing federated learning frameworks for multi-institutional collaboration while preserving data privacy. The integration of emerging neural architectures, particularly Transformer modules with attention mechanisms, promises to improve long-range dependency modeling in image reconstruction. Simultaneously, optimizing implicit neural representations through efficient encoding strategies could make scan-specific optimization clinically practical [15].

Establishing comprehensive evaluation standards represents another critical pathway forward. Future work should develop assessment frameworks that extend beyond conventional metrics to include diagnostic relevance and pathological fidelity. The creation of large-scale, multi-vendor benchmarks with expert annotations will be essential for validating clinical utility and ensuring reliable performance across diverse patient populations and imaging scenarios.

5. Conclusions

This review systematically charts the evolution from traditional sequential estimation to deep learning-enabled joint reconstruction of coil sensitivity and image in parallel MRI. Modern networks demonstrate that synergistic optimization of sensitivity maps and image content significantly improves reconstruction fidelity, robustness under high acceleration, and preservation of high-frequency details. Nevertheless, challenges in generalization, interpretability, and clinical validation remain. Future progress in this field will rely on advances in data-efficient learning, seamless integration of physical models with emerging neural architectures, and the establishment of standardized clinical evaluation frameworks, collectively enabling the development of intelligent, rapid, and reliable MRI reconstruction systems.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

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