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Optimizing Signal-to-Noise Ratio in MRI Using Fourier-Based Algorithms

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Abstract: Signal-to-noise ratio (SNR) is a critical determinant of image quality and diagnostic utility in Magnetic Resonance Imaging (MRI). Fourier-based techniques offer computationally efficient methods to optimize SNR without extending scan duration or requiring any hardware upgrades in some way. This review systematically analyzes and compares six primary Fourier-based SNR optimization methods: (1) frequency-domain filtering, (2) k-space manipulation, (3) spectral subtraction, (4) coil combination, (5) compressed sensing, and (6) transform-domain denoising. Each method is discussed regarding its underlying mathematical principles and practical implementation, and quantitative and qualitative effectiveness is demonstrated, as reported in some representative reviews. Results indicate substantial SNR improvements, often exceeding 40%, accompanied by enhanced anatomical clarity and contrast preservation. Among the reviewed techniques, spectral subtraction, optimal coil combination, and compressed sensing stand out for their significant SNR gains without compromising spatial resolution. The discussion also highlights trade-offs, such as balancing noise reduction against resolution and adaptability under varying MRI conditions. The essay concludes by emphasizing Fourier-based approaches' ongoing relevance and potential, particularly when integrated with emerging computational strategies such as artificial intelligence. Future developments promise advancements in MRI image quality, patient throughput, and diagnostic accuracy.

Keywords: Image reconstruction, Noise reduction, Magnetic image Resonance

1. Introduction

Magnetic Resonance Imaging (MRI) is renowned for its exquisite soft-tissue contrast, but the quality of an MR image is limited by its signal-to-noise ratio (SNR). SNR in MRI represents the strength of the actual signal (from tissue) relative to the background noise. High SNR images reveal fine anatomical details and subtle pathologies, whereas low SNR images appear grainy and can obscure essential findings. Consequently, there is strong motivation to optimize SNR through algorithmic techniques, ensuring that as much proper signal as possible is preserved and noise is suppressed without slower imaging.

In MRI, the raw data are collected into the Fourier domain (k-space), the key approach for many SNR enhancement strategies. Noise in MRI k-space is typically uncorrelated and has uniform power across frequencies. Frequency-domain filters can exploit this property. For instance, applying a low-pass filter or apodization in k-space can reduce high-frequency noise. Such filtering is conceptually like in CT reconstructions [1].

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An early MRI study showed that appropriate filtering of 2D Fourier data yields images with a more uniform noise texture closer to ideal white noise, which is preferable for human hearing [1]. Modern implementations of k-space filtering, like the Hamming or Gaussian filters, continue to boost SNR in fast MRI sequences. An example of Fourier-based SNR optimizations involves parallel imaging techniques, such as accelerated scans using multiple coil outputs. Here, mathematical algorithms in the Fourier domain can help reclaim SNR, and penalties are involved due to data reduction.

A notable approach is the optimal coil combination method. Instead of a simple sum-of-squares of coil images, one can combine coil data by weighting them based on coil sensitivities and noise correlations [2]. This effectively maximizes SNR for each pixel and yields a more uniform image. Algorithms like the adaptive combine (a subspace-based coil combine) operate on Fourier-transformed data from each coil to find the best composite image [2]. By doing so, they improve SNR through more innovative use of frequency-domain information.

Furthermore, compressed sensing (CS) uses iterative Fourier-domain reconstruction to denoise through sparsity constraints. CS-MRI uses the fact that MRI images often have sparse representations (in wavelet domains or gradient domains) and fills in missing k-space points in a way that eliminates noise-like incoherent artifacts. The result is faster imaging with SNR increases. In other words, this is an SNR optimization when time is limited. Once an image is reconstructed, post-processing algorithms can further enhance SNR, for instance, Wavelet-based denoising, where wavelets can be seen as a multi-scale extension of Fourier, and thresholding wavelet coefficients corresponds to removing noise frequencies while keeping important image features [3].

Techniques like wavelet shrinkage have demonstrated the ability to boost SNR in MRI images substantially [4]. For instance, a wavelet-Radon algorithm specifically targeted the Rician noise in low-intensity regions by operating in a transformed domain, leading to cleaner images with preserved edges [3].

More recently, deep learning denoising has improved. Deep neural networks can be trained to recognize and remove noise, learning a content-aware optimal frequency filter. These data-driven approaches have reported impressive SNR improvements, doubling the number of averages in a scan [5].

The significance of optimizing SNR in MRI cannot be overstated. Higher SNR improves images' visual clarity and reliability in quantitative analyses. Importantly, algorithmic SNR enhancement can enable lower-field MRI systems or faster imaging protocols to achieve diagnostic-quality results [6].

This essay will delve into the Fourier-based and related algorithms developed to push MRI's SNR to its limits. The paper examines evidence of the effectiveness of different algorithms and discusses their trade-offs. With these, the MRI community expects to move closer to the ideal of higher SNR imaging, maximizing the information content that MRI can provide.

2. Literature review

This review section will summarize the key methods, including frequency-domain filtering, k-space splicing, spectral noise subtraction, optimal multi-coil combination, compressed sensing reconstructions, and transform-domain denoising (e.g., using Fourier or DCT transforms).

$$SNR = \frac{\mu_S}{\sigma_N} \tag{1}$$

Where μ_s is the mean signal intensity and σ_n is the standard deviation of noise, plays a pivotal role in determining image quality. This section reviews Fourier-based techniques for SNR optimization, focusing on their mathematical interpretation and signal-processing strategies [1].

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2.1. Frequency-domain filtering

Frequency-domain filtering aims to suppress noise in k-space by attenuating high-frequency components, assuming that noise is spectrally flat (white) while signal energy is concentrated in low frequencies. The typical filtering operation in the Fourier domain can be represented as

$$\tilde{F}(u,v) = H(u,v) \times F(u,v) \tag{2}$$

Where F(u, v) is the 2D Fourier transform of the original image, H(u, v) is the filter function (e.g. Gaussian), and $\tilde{F}$(u, v) is the filtered frequency representation. The corresponding denoised image is recovered using the inverse Fourier transform:

$$\tilde{f}(u,v) = F^{-1}[\tilde{F}(u,v)] \tag{3}$$

The choice H(u, v) of dictates the trade-off between resolution and noise suppression. For example, a Gaussian filter in k-space:

$$H(u,v) = \exp\left(-\frac{u^2+v^2}{2\sigma^2}\right) \tag{4}$$

2.2. K-space manipulation and gain splicing

An innovative approach to optimizing SNR involves adjusting the receiver gain during acquisition to emphasize weaker k-space signals. Let represent k-space acquired with gain factor g_k, such that:

$$F_k(u,v) = g_k\, F(u,v) + N_k(u,v) \tag{5}$$

Where $N_k(u,v)$ is the noise introduced at gain g_k. In k-space splicing, data from different gain levels are normalized:

$$\widetilde{F_k}(u,v) = \frac{F_k(u,v)}{g_k} \tag{6}$$

These normalized components are then combined to construct a final composite k-space:

$$F_{composite}(u,v) = \sum_{k=1}^{K} \omega_k(u,v) \times \widetilde{F_k}(u,v) \tag{7}$$

Where $\omega_k(u,v)$ are spatial weights ensuring smooth transitions between regions. This method increases the dynamic range of signal acquisition, especially in peripheral k-space, leading to improved SNR after reconstruction [7].

2.3. Spectral subtraction

Spectral subtraction denoising (SSD) operates on the assumption that noise power can be estimated and subtracted in the frequency domain. Given a noisy signal spectrum $P_Y(u,v)$, the noise power spectrum $P_N(u,v)$ is estimated, and the signal power is obtained by:

$$P_X(u,v) = \max\left(P_Y(u,v) - P_N(u,v), 0\right) \tag{8}$$

The denoised spectrum can then be reconstructed as:

$$\tilde{F}(u,v) = \sqrt{P_X(u,v)}\, \exp\left(\varphi_Y(u,v)\right) \tag{9}$$

Where $\varphi_Y(u,v)$ is the original phase of the noisy spectrum. This method retains phase while suppressing noise amplitude, preserving structural detail in the reconstructed image [6].

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2.4. Optimal coil combination

In parallel MRI, multi-channel receives coils provide independent measurements, each with its own sensitivity $s_i(x,y)$ and noise covariance $\sum_{ij} 1$. The optimal linear combination of N coil $f_j(x,y)$ to maximize SNR is:

$$f_{opt}(x,y) = \frac{\sum_{i,j=1}^{N} s_i(x,y) \, \sum_{i,j=1}^{-1} f_j(x,y)}{\sqrt{\sum_{i,j=1}^{N} s_i(x,y) \, \sum_{i,j=1}^{-1} s_j(x,y)}} \tag{10}$$

This formulation yields the maximum SNR image estimate under Gaussian noise assumptions.

2.5. Compressed sensing and sparse reconstruction

Compressed sensing (CS) leverages the sparsity of MRI images in a transform domain (e.g., wavelets, total variation) to reconstruct from under-sampled k-space:

$$\max_{x} \|\psi_x\| \ subject \ to \ \|Ax - y\| \leq \varepsilon \tag{11}$$

Where x is the image, y is the under sampled k-space data, A is the encoding operator, and ε accounts for noise.

This formulation reduces aliasing and incoherent artifacts, effectively improving SNR in the reconstructed image without needing full data [8].

2.6. Transform-domain denoising

Transform-based denoising methods, such as wavelet shrinkage or discrete cosine transform (DCT) filtering, transform the image to a domain where signal and noise are more separable. For instance, in wavelet threshold:

$$\widetilde{\omega_{i,j}} = \begin{cases} \omega_{i,j} - \lambda \cdot sign(\omega_{i,j}), \ if \left|\omega_{i,j}\right| > \lambda \\ 0, \ otherwise \end{cases} \tag{12}$$

where $\omega_{i,j}$ are wavelet coefficients, λ is a noise-dependent threshold, and $\widetilde{\omega_{i,j}}$ are denoised coefficients. The image is reconstructed via inverse wavelet transform:

$$\tilde{f}(x,y) = W^{-1}[\widetilde{\omega_{i,j}}] \tag{13}$$

This approach suppresses noise-dominated components while preserving meaningful structures, especially in high-frequency image regions [6].

3. Methodology

Consider the literature review, which followed a systematic approach to identify and analyze relevant studies on Fourier-based SNR optimization in MRI. Now, this section will search scholarly databases (PubMed, IEEE Xplore, and Google Scholar) using keywords such as "MRI SNR optimization," "Fourier transform denoising," "k-space SNR," "spectral subtraction MRI," and "compressed sensing MRI."

The search was focused on high-impact conference papers from roughly the last 20 years to capture recent advances. From an initial pool of over 100 papers, this paper filtered down to about 20 core studies that explicitly employed frequency-domain or transform-domain techniques to improve the SNR of MRI. The selected articles were then reviewed in detail and grouped into thematic categories reflecting the different Fourier-based strategies. The following section will compile each category's key findings and qualitative outcomes, such as whether a given method preserved finer details or

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introduced blurring or anti-facts. This comparative analysis enabled us to identify trade-offs and the level of enchantment in optimizing MRI SNR, as summarized in the review.

4. Results

The selected studies report improvements in MRI SNR using a range of Fourier-based techniques. Both quantitative gains and qualitative enhancements are observed. Below, we summarize these results by method category, and Table 1 provides a comparative overview of each technique's key outcomes.

Table 1: Summary of Fourier-based SNR optimization methods and improvements across studies

Algorithm (Category)	Main Mechanism	SNR improvements	Qualitative Effects
Frequency-domain	Cross-correlate two images' Fourier spectra to estimate true signal	3.24→6.03 with resolution loss ~26% [9]	Slight blurring, noise greatly reduced with details largely preserved.
K-space manipulation	Multiple acquisitions with different receiver gains for center vs. periphery of k-space, followed by normalized splicing k-space, followed by normalized splicing	Increased by 5~13% [7]	Clearer visualization of low-signal details; more uniform noise distribution (no resolution loss).
Spectral subtraction (SSD)	Subtract estimated noise power spectrum from each coil's k-space data prior to image reconstruction	Increased up to 45% (40% in vivo) [8]	Smoother images: edges and fine structures maintained, with improved detail vs. diffusion filtering [8].
Adaptive coil combination (Coil signal fusion)	Per-pixel weighted combine of multi-coil images, matched-filter to maximize local SNR	Increased by sum-of-squares of baseline [2]	More uniform image intensity (reduced coil bias); better tissue contrast than SoS combine [2]
Subspace coil combination (Coil signal fusion)	MMSE-based optimal coil weighting via subspace decomposition	7 times higher vs. conventional coil combines [11]	Virtually no intensity inhomogeneity; high-contrast, very low-noise images across FOV.
Sparse MRI (Compressed sensing)	Random under sampling of k-space with iterative recon enforcing wavelet sparsity (ℓ1-norm)	+41–42 dB (PSNR) under 25% data [10];	Almost no aliasing artifacts; sharp edges and textures preserved (similar quality to fully sampled image) [10].
Adaptive CS (Compressed sensing)	Optimized k-space sampling pattern with patch-based dictionary sparsity in reconstruction	+7 dB PSNR VS non-adaptive CS [11]	Noticeably cleaner reconstructions: suppressed incoherent alias noise; subtle features recovered despite heavy under sampling [11].
Wavelet packet denoising (Transform-domain)	Wavelet packet thresholding (performed on complex MRI data before magnitude calculation)	increased significantly vs. no filtering [12]	less blurring and enhanced low-contrast detail vs. standard magnitude-image denoising [12]
BM4D nonlocal filter (Transform-domain)	4D block-matching filter (frames similar patches, transforms to denoise, handles Rician noise via pre-stabilization)	Reported to maximally improve in volumetric MRI [6]	Yields very smooth yet detailed images; noise virtually eliminated without over-smoothing [6]

5. Discussion

Despite encouraging improvements, the current Fourier-based SNR optimization methods and the literature studying them have several limitations. A recurring theme is the trade-off between noise suppression and image resolution. Some reviewed papers quantified this trade-off; for example, low-pass filtering did not improve the frequency-dependent SNR because it attenuates signal and noise equally [1]. Spectral subtraction was noted to preserve resolution better [8], but it, too, assumes noise can be characterized and subtracted perfectly. Another limitation is the method's applicability across different conditions. Denoising algorithms often require tuning parameters that are dataset-specific, such as threshold levels and filter shapes, and their performance can degrade on different anatomies or scanner settings. For instance, wavelet denoising algorithms that worked well for brain images

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might need re-optimization for body MRI due to different texture statistics. Likewise, compressed images that yield excellent results for angiography might struggle for abdominal imaging due to different sparsity characteristics. Another concern is the dependency on specific data types or hardware. Coil combination methods obviously require multi-coil data; the SNR gains disappear if only a single coil is available. Some advanced k-space techniques assume consistent phase information, like partial Fourier, which assumes conjugate symmetry from a homogenous object, which may not hold if motion or field inhomogeneity is present. Moreover, some methods demand highly computational resources or expertise that are unavailable in all clinics. For example, iterative CS or Artificial Intelligence (AI) reconstructions can be time-consuming or require GPU acceleration, making them harder to deploy for every patient in a busy hospital setting. Finally, a limitation in the research field is that each technique is often developed and evaluated in isolation. There is a lack of head-to-head comparisons under standardized conditions. However, our Results included a comparative table of 10 papers. Differences in datasets and metrics make it hard to declare an overall "winner." The community would benefit from more unified benchmarks to assess the best SNR optimization approaches.

In real-world applications, a key consideration is how these Fourier-based SNR optimization methods perform under these real-world MRI constraints. During clinical imaging, scan time is often at a premium. In scenarios where scan time cannot be extended, a combining strategy is applied. Multi-coil receiver hardware is ubiquitous, which makes coil combination techniques immediately applicable. Phased-array coil combination is standard in virtually all clinical MRI protocols; it directly increases SNR by pooling signals from multiple coils covering the region of interest. Field strength is another crucial factor. At high field (3T and above), the baseline SNR is high, so mild Fourier filtering or denoising can be enough to suppress noise without visibly degrading detail. Conversely, intrinsic SNR is poor in a low field (smaller than 0.5T), making advanced SNR recovery techniques helpful and often necessary. The literature suggests that sophisticated reconstruction methods can salvage image quality in low-field settings where conventional Fourier methods fail. For example, one study of a 6.5 mT MRI showed that a deep learning reconstruction (which operates partly in the Fourier domain) improved SNR 1.5 to 4.5 times over standard Fourier reconstruction [13]. Methods like spectral subtraction and transform-domain denoising are generally compatible with existing workflows, but hardware limitations also determine which techniques are feasible. Ultimately, the clinical applicability of these methods is about choosing the right tool for the constraint at hand: for faster scans, compressed sensing or parallel imaging plus denoising is effective; for low-field or low-SNR cases, heavy-duty Fourier-domain reconstructions (possibly learning-based) can recover lost SNR; for high-detail diagnostic needs, one would apply only gentle filtering to avoid blurring critical pathology. However, in resource-limited or portable MRI setups (e.g., low-field, few coils), one cannot rely on coil count or brute-force averaging to boost SNR.

Rather than viewing the various Fourier-based SNR enhancement methods in isolation, it is insightful to consider how they can complement each other within an imaging pipeline. These techniques can be combined synergistically to capitalize on their strengths while offsetting individual weaknesses. A pragmatic approach is to use multiple tools in concert: for example, employ hardware-based enhancements (coils, fast sequences) and then apply software-based enhancements (such as filtering, subtraction, CS) as needed. For example, the multi-coil acquisition provides an initial SNR boost via hardware; on top of that, one could apply spectral subtraction or transform-domain denoising to each coil's data before a combination [8]. This pairing leverages the coil array's SNR gain and the algorithm's noise suppression, resulting in an image superior to either technique alone. Another complementary approach is using compressed sensing with spatial/frequency filtering. Compressed sensing reconstructions inherently include a form of denoising through regularization, but residual noise can still be present, especially at higher acceleration factors. A gentle Fourier-

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domain filter or a wavelet denoiser applied after CS reconstruction can clean up this residual noise floor.

Conversely, one could integrate the denoising into the reconstruction. For instance, some techniques perform an initial k-space noise filtering (to stabilize the inversion problem) followed by image-domain refinement for artifact removal. The idea is to address noise at multiple stages: remove high-frequency noise early on, then correct any blurring or artifacts with an image-domain process. Such multi-stage pipelines can yield spotless yet sharp images, effectively combining the benefits of frequency filtering and spatially adaptive denoising. This complementary use of techniques is likely the path forward for pushing MRI image quality to new heights under practical constraints. The advent of machine learning would further enable the integration of methods. Deep learning models can be trained to simulate Fourier-based operations to apply an optimal k-space filter and image-domain enhancement in a constructed model. A recent trend is AI-driven reconstruction frameworks that take raw k-space data and produce high-SNR images by learning from examples. These often incorporate the Fourier transform as a layer or use knowledge of k-space in the network architecture, merging data-driven learning with physical modeling [5]. For instance, one could envision a comprehensive workflow: advanced k-space sampling (like radial or spiral trajectories to inherently average noise), plus parallel imaging (to cut time), then Fourier-domain noise subtraction on each coil, followed by a multi-coil combine, and finally a transform-domain cleanup (wavelet or AI-based) on the reconstructed image.

6. Conclusion

SNR plays a key role in determining the quality and usefulness of MRI images. A higher SNR means more explicit images and more accurate diagnoses. This review has shown that many Fourier-based methods can boost SNR effectively. These improvements do not require more advanced hardware or longer scan times. Instead, they rely on more innovative ways of processing the data. Some of the most effective techniques include k-space filtering, combining signals from multiple coils, removing unwanted frequency components, using compressed sensing, and applying denoising in the transform domain. Each method brings its advantages and can be adapted to different clinical needs. Examples include filtering in k-space to remove unwanted noise and combining signals from multiple coils to strengthen the overall signal. Other methods involve spectral subtraction, which reduces noise by targeting specific frequency ranges, and compressed sensing, which reconstructs images clearly from fewer measurements. Finally, transform-domain denoising eliminates noise directly from the transformed image data. When applied appropriately, these methods improve image clarity imaging construction.

Fourier-based methods make Fourier transforms not just a mathematical tool but also an SNR optimization technique grounded in the Fourier domain. Importantly, these algorithms enable enhancements in image quality without altering scan parameters or requiring new hardware, which is particularly valuable in settings where accessing cutting-edge equipment is limited. AI with Fourier-domain processing is one of the most promising avenues for future research. AI-driven reconstruction models can dynamically learn and optimize noise suppression, tailoring filtering strategies to specific anatomy, scan types, or acquisition settings.

In clinical practice, the goal is to improve image quality and complete the process rapidly without introducing artifacts or bias. To that end, future development should focus on creating robust, generalizable algorithms that perform well across various scanners and imaging protocols, have tangible benefits in diagnosis, and further improve patient care.

In conclusion, optimizing MRI's SNR through Fourier-based algorithms is a mature but still evolving field. These methods enable cleaner, sharper images while reducing the acquisition time. As technology progresses, combining classical signal processing and intelligent computation will continue to enhance MRI's power and accessibility, ultimately leading to better imaging outcomes across a broad range of clinical environments.

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