Evolution of Methods for Mitigating Spacecraft-Generated Magnetic Interference

Introduction

Spacecraft magnetometers provide measurements necessary for investigating planetary magnetic environments, solar-wind interactions, magnetospheric dynamics, and other processes in space physics. A persistent challenge, however, is that a magnetometer measures not only the natural magnetic field surrounding a spacecraft, but also magnetic fields generated by the spacecraft itself. Electrical currents, instruments, structural materials, attitude-control systems, and other onboard subsystems can contribute to the signals that overlap the geophysical measurements of interest. Separating these contributions has therefore remained both an instrumentation and signal-processing problem for more than five decades.

Historically, missions addressed spacecraft-generated magnetic contamination primarily through magnetic cleanliness programs, long instrument booms, and gradiometry. These strategies use physical knowledge of the spacecraft and the spatial decay of locally generated magnetic fields. Although effective under appropriate conditions, their assumptions become increasingly difficult to satisfy as spacecraft become smaller, sensor separation decreases, and onboard systems produce complex and time-varying magnetic signatures. The development of CubeSats and other resource-constrained spacecraft has consequently motivated signal-processing methods that can operate when traditional magnetic cleanliness and boom configurations are impractical.

The literature reflects a corresponding evolution in interference-mitigation strategies. Early methods relied primarily on **physical models and sensor geometry**. Later techniques incorporated **spacecraft telemetry, statistical relationships between sensors, blind source separation, time-frequency representations, and machine learning**. These developments provide increasing flexibility, but they do not remove the assumptions required to distinguish interference from the desired signal. Instead, assumptions concerning spacecraft geometry and magnetic-field decay are progressively replaced by assumptions concerning statistical independence, correlation, sparsity, training data, or identifiable signal structure.

This review asks: **How have methods for mitigating spacecraft-generated magnetic interference evolved to address the limitations of traditional gradiometry?** The works are organized into four methodological themes: physics-based gradiometry, operational and statistical alternatives, complex interference separation, and validation. Particular attention is given to how the methods differ in the information they use, the assumptions they impose, and the degree to which they preserve a physically meaningful magnetic-field measurement.

Physics-Based Approaches: Gradiometry and Magnetic Cleanliness

Early spacecraft magnetic-field measurements relied heavily on engineering practices designed to reduce contamination before the data were collected. Magnetic cleanliness programs use material selection, controlled electrical design, subsystem testing, magnetic mapping, and careful magnetometer placement to limit spacecraft-generated magnetic fields. Magnetometers

are also commonly positioned on booms so that their distance from local spacecraft sources improves discrimination between spacecraft and ambient magnetic fields (Acuña, 2002).

Ness et al. (1971) provided the foundational dual-magnetometer gradiometer framework used by many subsequent missions. Two magnetometers positioned at different distances from the spacecraft measure approximately the same ambient magnetic field but different amplitudes of locally generated spacecraft interference. By describing how the spacecraft field changes with distance, the spacecraft contribution can be estimated and the ambient field recovered.
The primary strength of the Ness approach is its **physical interpretability**. Signal separation is based on a known spatial relationship rather than solely on statistical behavior. However, the approach also depends on assumptions about how the spacecraft magnetic field scales between sensors.

Neubauer (1972) examined a related but distinct problem: how magnetometer geometry affects the accuracy of the gradiometer system. Whereas Ness et al. established the basic separation principle, Neubauer focused on the number of magnetometers, their positions, and boom length. The work showed that greater distance from the spacecraft and increased separation between sensors generally improve the ability to distinguish the spacecraft field from the ambient field. The optimal sensor configuration therefore depends on both spacecraft magnetic properties and structural constraints.

Mehlem (1978) challenged another assumption underlying simple gradiometer models. A spacecraft contains multiple magnetic components at different locations and orientations, and its magnetic field may not be represented accurately by a single centered dipole. By considering multiple magnetic dipoles, Mehlem demonstrated that even physically grounded gradiometry can become inaccurate when the assumed source model oversimplifies the spacecraft.

Together, Ness, Neubauer, and Mehlem established the physical basis and major limitations of traditional gradiometry. Ness et al. contributed the fundamental separation framework, Neubauer clarified the importance of sensor geometry, and Mehlem demonstrated the need to account for source complexity. Of these contributions, **Ness et al. (1971) has the greatest foundational significance**, because later multimagnetometer approaches continue to rely on the central observation that spacecraft-generated magnetic fields vary spatially while the ambient field is approximately shared between nearby sensors. Neubauer and Mehlem are particularly valuable because they clarify the conditions under which that assumption succeeds or fails.

The strength of these early methods is therefore not simply that they remove interference. They connect interference mitigation directly to the physics of the measurement system. Their principal limitation is that spacecraft geometry, magnetic cleanliness, and source structure must be sufficiently well characterized.

Operational, Adaptive, and Statistical Alternatives

As spacecraft designs became less constrained by magnetic cleanliness requirements, researchers began exploring approaches that relied less heavily on predetermined spacecraft magnetic models.

Pope et al. (2011) represents an important transition in the literature. Using Venus Express measurements, the authors addressed spacecraft-generated interference on a platform that had not undergone the same extensive magnetic-cleanliness program associated with earlier missions. Rather than relying exclusively on a dipole model, the approach used differences between inboard and outboard magnetometer measurements, statistical properties of observed disturbances, and spacecraft housekeeping information.

This represented a conceptual shift. Instead of assuming that the entire spacecraft magnetic environment had to be characterized beforehand, Pope et al. treated **patterns in the measured interference itself** as useful information. Disturbances could be related to heaters, solar-array motors, antennas, reaction wheels, and other spacecraft systems by combining magnetic measurements with operational knowledge.

Allen et al. (2014) extended this idea by using current telemetry to model magnetic contamination generated by spacecraft electrical systems. The advantage is that known spacecraft currents provide direct information about possible magnetic sources. However, the method depends on accurate, sufficiently sampled telemetry and on stable relationships between electrical behavior and magnetic contamination.

Sheinker and Moldwin (2016) moved further away from explicit spacecraft modeling through adaptive interference cancellation. Their approach uses a pair of magnetometers exposed to different levels of the same contamination. Instead of deriving the spacecraft contribution from a physical field model, correlated interference between measurements is adaptively estimated and removed.

These three approaches address similar limitations of classical gradiometry, but they do so using different information. **Pope et al. use statistical signatures together with operational context; Allen et al. use spacecraft telemetry; Sheinker and Moldwin use intersensor correlation.** Each reduces dependence on complete magnetic characterization but introduces a different assumption about what information is available and reliable.

Pope et al. (2011) is particularly important because it demonstrates that useful scientific magnetic-field measurements can still be obtained from a magnetically unclean spacecraft. In this sense, the study makes one of the strongest conceptual contributions after Ness et al.: it expands the problem from one of spacecraft design to one of data analysis and system characterization.

At the same time, these methods reveal a recurring pattern. **Relaxing a physical assumption does not create an assumption-free algorithm.** Instead, the method becomes dependent on telemetry quality, statistical relationships, operational knowledge, or correlations between sensors.

Statistical Source Separation and Boomless Approaches

The increasing use of small spacecraft has intensified interest in methods capable of operating with short or absent booms. In these configurations, traditional spatial gradiometry becomes less effective because all magnetometers may lie relatively close to spacecraft interference sources.

Constantinescu et al. (2020) proposed a maximum-variance gradiometer approach that combines physical sensor placement with statistical decomposition. Principal component analysis and transformation matrices are used to distinguish spacecraft-generated disturbances from a relatively clean reference measurement. This approach maintains a connection to multimagnetometer gradiometry while using the statistical structure of the data to improve separation.

The method is attractive because it bridges physical and statistical reasoning, but it depends on assumptions concerning disturbance polarization and dominant-source behavior. These assumptions are suitable for some current-driven magnetic sources but become less reliable for more complicated sources such as rotating reaction wheels whose magnetic signatures may project across multiple field components.

Imajo et al. (2021) approached the problem using independent component analysis. Rather than requiring explicit knowledge of each interference source, ICA separates observed measurements into components that are maximally statistically independent. This makes it attractive for boomless magnetic measurements in which detailed source information is unavailable.

However, ICA replaces physical modeling assumptions with a strong statistical requirement: the contributing sources must be sufficiently independent. The number of identifiable components is also constrained by the available measurements. As a result, performance may decline when multiple interference sources overlap or when ambient and spacecraft-generated signals are not statistically separable.

Hoffmann and Moldwin (2022) addressed one of these limitations through underdetermined blind source separation, designed for cases in which the number of sources may exceed the number of sensors. Their method exploits structure in the time-frequency domain, where points associated with individual sources can form clusters. Density-based clustering is used to estimate source relationships, followed by compressive sensing to reconstruct signals under sparsity assumptions.

Hoffmann et al. (2023) subsequently extended the framework using the Quad-Mag multi-sensor system and an improved underdetermined blind source separation algorithm. A related method, WAIC-UP, uses relationships among wavelet coefficients to identify and suppress interference in compact spacecraft configurations (Hoffmann & Moldwin, 2023).

These approaches are similar in that they attempt to separate sources **without detailed prior knowledge of spacecraft subsystems**. They differ primarily in what mathematical property defines separability. Constantinescu et al. rely on variance and polarization structure, Imajo et al. rely on independence, and Hoffmann and colleagues rely on clustering, sparsity, and transformed-domain structure.

Among these approaches, the Hoffmann work makes a particularly important contribution to the development of boomless spacecraft magnetometry because it explicitly addresses cases in which simple one-source or one-sensor assumptions are inadequate. However, its flexibility comes with the cost of stronger representation-dependent assumptions. If interference is not sparse or does not form separable structures in the chosen domain, performance can deteriorate.

The comparison therefore reinforces a central conclusion of the literature: statistical source-separation methods are not simply replacements for gradiometry. They represent alternative definitions of what makes two signals distinguishable.

Reaction Wheel Interference and the CASSIOPE/e-POP Case

Reaction wheels provide a useful test case because their interference is structured rather than random. Reaction wheels are used to control spacecraft attitude, and their rotating components can produce quasi-periodic magnetic signatures. As wheel speed changes, the observed magnetic frequency changes as well. Harmonics may also appear at integer multiples of the fundamental wheel frequency.

The CASSIOPE/e-POP mission has become an important dataset for studying this problem. Its Magnetic Field Instrument uses two triaxial fluxgate magnetometers located on a relatively short boom. The configuration provides some spatial information, but the limited separation makes conventional gradiometry less effective for the strong time-varying reaction-wheel signatures present in the data.

Finley et al. (2023a) addressed the problem using Multichannel Singular Spectrum Analysis. M-SSA decomposes multichannel time-series measurements into temporal components. Measurements from multiple sensors and magnetic-field axes are considered simultaneously, allowing components associated with interference to be distinguished from components associated with the geophysical background.

In the CASSIOPE application, an approximate spacecraft-interference signal is generated using differences between magnetometer measurements. Reconstructed components are then compared with that approximation, and components correlated with interference are excluded from the recovered signal.

The principal advantage of M-SSA is that it provides a path from signal decomposition back to a reconstructed time series. Finley et al. reported substantial reduction of reaction-wheel interference while preserving recognizable geophysical features. However, the method remains sensitive to the selected analysis window and to overlap between interference and natural signals. When different physical sources occupy similar regions of the data, statistical decomposition may not assign them cleanly to separate components.

Finley et al. (2023b) extended this approach by combining SSA/M-SSA decomposition with a convolutional neural network. Multimagnetometer information was used to label decomposed components, which were then used to train a classifier capable of identifying

interference automatically. This reduces the need for continuous dual-sensor availability and offers a scalable approach for large datasets.

The supervised method is more automated than M-SSA alone, but it inherits limitations from the decomposition stage and introduces additional dependence on representative training data. The CNN may classify learned signal structures accurately within the training domain while still struggling when spacecraft configuration, interference characteristics, or geophysical conditions change.

Finley et al. (2024a) further extended the data-driven framework using principal component analysis and unsupervised anomaly detection. Unlike the earlier interference-removal techniques, this approach primarily identifies unusual intervals rather than necessarily reconstructing a cleaned magnetic field. It therefore addresses a related but distinct scientific need: locating intervals that deserve additional investigation or exclusion.

These Finley studies demonstrate a progression from statistical decomposition toward increasingly automated classification. Their greatest contribution is showing that **multichannel statistical structure can support both interference mitigation and automated analysis of operational spacecraft data**. M-SSA is especially persuasive because it provides measurable interference reduction while retaining a reconstruction pathway.

Time-Frequency Structure and the Sen Gupta & Miles Framework

Sen Gupta and Miles (2023) approach reaction-wheel interference differently. Instead of decomposing the time series into statistically distinct components, they treat interference identification as a feature-extraction problem in the time-frequency domain.
Reaction-wheel rotation rates evolve continuously rather than changing instantaneously. Their magnetic signatures therefore form narrowband trajectories in spectrograms, and associated harmonics can appear at related frequencies. Sen Gupta and Miles exploit this continuity along with differences between the two magnetometers and redundancy among the three vector components.

This approach differs fundamentally from M-SSA. **Finley et al. ask whether a signal can be separated into statistically distinguishable temporal components; Sen Gupta and Miles ask whether interference can be recognized through its spectral morphology.** The two approaches therefore use different definitions of structure.

The Sen Gupta and Miles framework is particularly valuable because it demonstrates that reaction-wheel interference contains information beyond amplitude. Continuity, harmonic relationships, and multisensor redundancy all reflect the physical behavior of the rotating system. In the CASSIOPE data, these features make the reaction-wheel signatures visually distinguishable from much of the geophysical background.

At the same time, spectral identification introduces a distinction between **detection and reconstruction**. A time-frequency representation can make an interference feature easy to identify without necessarily preserving the mathematical structure required to reconstruct a physically meaningful magnetic-field time series after modifying that feature. Combining

spectral information from different sensors or axes may improve feature visibility but can also disrupt phase relationships or vector consistency.

For this reason, the strongest contribution of Sen Gupta and Miles is not necessarily that the method represents a complete solution to interference removal. Rather, it demonstrates that **physically generated interference possesses structured time-frequency characteristics that can be exploited as discriminating information**.

More recent work by Shi et al. (2025) strengthens this direction by examining instantaneous phase discontinuities as an indicator of overlapping magnetic-field signals. Traditional spectral methods commonly emphasize magnitude or power, but phase can retain additional information about the relationships among superimposed signals. Shi et al. therefore expand the set of features that may be useful when magnitude-based separation becomes ambiguous.

Sen Gupta and Miles and Shi et al. are complementary in this respect. The former emphasizes continuity and harmonic morphology, while the latter demonstrates the potential value of phase behavior. Together, they suggest that interference separation may benefit from considering complex signal structure rather than relying on amplitude alone.

Validation and the Preservation of Scientific Information

As interference-mitigation techniques become more sophisticated, a new question becomes increasingly important: **How can researchers determine whether a cleaned signal accurately represents the original geophysical field?**

Operational spacecraft data generally do not provide a known uncontaminated version of the ambient magnetic field. Consequently, successful disappearance of an interference feature does not prove that the desired signal has been preserved. An algorithm may suppress reaction-wheel signatures while also attenuating or modifying natural fluctuations occupying the same time, frequency, or statistical subspace.

Hoffmann et al. (2024) address this broader methodological challenge through MAGPRIME, an open-source framework for benchmarking magnetic-interference mitigation algorithms. Standardized benchmarking is especially valuable because the approaches reviewed here are otherwise evaluated using different spacecraft, sensors, interference sources, and performance measures. A method that performs well in one study may therefore be difficult to compare directly with another.

Finley et al. (2024b) provide a complementary contribution through a controlled laboratory-generated dataset. In this environment, spacecraft-like interference and pseudo-geophysical signals can be generated under conditions in which their contributions are known independently. This produces something that operational spacecraft observations generally cannot provide: a ground truth for evaluating whether interference was removed without damaging the desired signal.

These validation-focused contributions may ultimately prove as important as the development of new mitigation algorithms themselves. MAGPRIME improves methodological

comparison, while the controlled dataset allows preservation of the desired signal to be evaluated directly.

For that reason, **benchmarking and ground-truth validation represent one of the strongest recent developments in the field**. The central question is no longer only whether interference has been reduced, but whether the recovered data remain scientifically trustworthy.

Comparative Synthesis

Across more than five decades of research, spacecraft magnetic-interference mitigation has progressed through several different definitions of signal separability.

Ness et al. (1971) demonstrated that sources can be distinguished through **spatial variation**. Pope et al. (2011) showed that **statistical behavior and operational context** can compensate when traditional magnetic cleanliness assumptions are weakened. Sheinker and Moldwin (2016) exploited **correlation between sensors**, while Imajo et al. (2021) used **statistical independence**. Hoffmann and colleagues used **sparsity, clustering, and transformed-domain structure**. Finley et al. demonstrated the value of **multichannel temporal decomposition and learned classification**, while Sen Gupta and Miles (2023) emphasized **spectral morphology and continuity**. Shi et al. (2025) expanded the discussion further by showing that **phase behavior** may provide information about overlapping signals.
These works are therefore less contradictory than complementary. Each identifies a different property that can distinguish one contributing signal from another.

The strongest approaches are those in which the assumed discriminating property has a clear relationship to the physical measurement problem. Traditional gradiometry remains particularly convincing because its separation mechanism is directly connected to spatial field decay. Its limitation is practical rather than conceptual: modern spacecraft may not provide sufficient separation or sufficiently simple magnetic environments.

Among later approaches, Pope et al. (2011) makes a major contribution by demonstrating that magnetic interference can be addressed systematically even when the spacecraft itself was not designed around strict magnetic cleanliness. Finley et al. (2023a) is compelling because it demonstrates substantial interference mitigation on operational spacecraft measurements while retaining a reconstruction framework. Sen Gupta and Miles (2023) contributes a different but equally important idea by demonstrating that reaction-wheel signatures can be treated as structured time-frequency features rather than generic noise.

More recent validation work may be the most important development for determining how these methods should be compared. Without ground truth or common benchmarking, a method that produces a visually cleaner spectrogram or lower interference amplitude cannot automatically be considered superior. The true objective is preservation of the scientific information contained within the measurement.

Research Gaps and Future Questions

The literature reveals several unresolved challenges.

First, **no single discriminating feature is reliable under all conditions**. Spatial decay becomes less useful on short-boom spacecraft. Statistical independence may fail when physical signals overlap. Sparsity may be representation-dependent. Learned classifiers may not generalize to new missions. Spectral morphology may become ambiguous when geophysical and spacecraft signals occupy the same region of time-frequency space.

Second, **physical information is not always incorporated into modern statistical methods**. Reaction-wheel interference is generated by a rotating physical system with constrained dynamics, spatial orientation, harmonic relationships, and relationships across sensors. These features may provide useful constraints in cases where purely statistical separation fails.

Third, **interference identification does not guarantee reconstructability**. Time-frequency feature extraction can identify contamination effectively while producing modified representations that no longer correspond to a physically realizable time series. Preservation of phase, temporal continuity, sensor relationships, and three-dimensional magnetic-field structure becomes essential when the objective is reconstruction rather than detection.

Fourth, **validation and generalization remain incomplete**. A method that succeeds on one spacecraft may depend strongly on that spacecraft's geometry, sampling rate, instrumentation, or interference environment. Benchmarking frameworks and controlled datasets provide important steps toward addressing this problem, but further cross-mission evaluation is necessary.

These limitations motivate several questions for continued research:

- Which physical and mathematical features most reliably distinguish spacecraft-generated interference from geophysical magnetic signals?
- Under what conditions are spatial, statistical, spectral, and phase-based features most useful?
- Can physical constraints and signal-processing methods be combined to resolve overlapping spacecraft and geophysical signals?
- How can interference be modified in the time-frequency domain while preserving a reconstructable vector magnetic-field measurement?
- How should interference rejection and preservation of scientific information be evaluated simultaneously?
- Which interference characteristics generalize across spacecraft and which remain mission-specific?

Conclusion

The development of spacecraft magnetic-interference mitigation has not followed a progression in which newer algorithms simply replace older ones. Instead, the field has accumulated multiple ways of extracting information about the sources contained within magnetometer measurements.

Ness et al. (1971) made the greatest foundational contribution by establishing spatial variation as a physically meaningful basis for separating spacecraft and ambient magnetic fields. Pope et al. (2011) made a major conceptual advance by showing that spacecraft interference can be characterized and corrected even when traditional magnetic-cleanliness assumptions are not satisfied. Statistical and blind-source-separation approaches subsequently expanded the range of spacecraft configurations that can be considered, while Finley et al. demonstrated the effectiveness of multichannel decomposition and machine-learning approaches for operational spacecraft data. Sen Gupta and Miles (2023) further contributed by treating reaction-wheel interference as a structured time-frequency phenomenon, and Shi et al. (2025) demonstrated that phase may provide additional information when signals overlap.

Taken together, the literature suggests that the most convincing future direction is not one based exclusively on physical modeling, statistical decomposition, machine learning, or spectral filtering. Each approach captures only part of the information available within a complex measurement. A more robust framework would combine **physically meaningful constraints with statistical and signal-processing representations while preserving the ability to reconstruct and validate the desired scientific signal**.

The most important advancement may therefore not be another isolated interference-removal algorithm, but a framework that determines which properties of the measurements remain trustworthy under different spacecraft conditions and quantifies how much scientific information is preserved after mitigation.

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