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Slice-timing and resampling in imaging

Clarifying Slice-Timing Correction, Motion Correction, Transform Composition, and Interpolation Kernels in Neuroimaging Preprocessing

Quick Reference

Key Findings Table

Topic	Key Evidence/Best Practice	Supporting Citations
STC vs. MC Order	Motion estimation should precede any temporal interpolation (e.g., STC) to avoid underestimating motion and biasing artifact detection. The optimal order of STC and MC is scan- and motion-dependent.	1 2
Transform Composition	Composing all spatial transforms (motion, SDC, EPI → anatomy, anatomy → template) into a single resampling step reduces interpolation artifacts and improves alignment.	3 4 5
Interpolation Kernels	Linear, cubic B-spline, Wendland, sinc (truncated/Lanczos), and Kaiser-windowed sinc are common. Wendland and cubic polynomial kernels can reduce effective smoothness and preserve high-frequency details better than cubic B-spline.	6 7 8
Adaptive SDC	Adaptive weighting in fieldmap-based SDC and spatially adaptive regularization in non-rigid registration improve correction in low-confidence/distorted regions.	3 9 10
Real-Time/Prospective MC	Prospective slice-by-slice MC and advanced slice-to-volume methods reduce false positives and improve statistical power in fMRI.	11 12

Direct Answer

- **Slice-timing correction (STC) should be performed after motion estimation (i.e., motion parameters should be estimated on the original data, before any temporal interpolation such as STC).** This preserves sensitivity to motion artifacts. The optimal order of STC and motion correction (MC) for resampling is scan- and motion-dependent, and may be adapted based on acquisition scheme (sequential vs. interleaved), TR, and motion magnitude.
- **Composing all spatial transforms (motion, SDC, EPI → anatomy, anatomy → template) into a single resampling step is strongly supported by evidence** to minimize interpolation artifacts and improve spatial alignment.

- **Common interpolation kernels**: linear, cubic B-spline, Wendland, cubic polynomial, truncated sinc (Lanczos), and Kaiser-windowed sinc. Wendland and cubic polynomial kernels can reduce effective smoothness and preserve high-frequency details better than cubic B-spline, but require careful parameterization.

Study Scope

- **Time period**: 2000–2024
- **Disciplines**: Neuroimaging, MRI physics, image processing, computational neuroscience
- **Methods**: Empirical studies, simulation, meta-analysis, algorithmic benchmarking, clinical validation

Assumptions & Limitations

- Most evidence is derived from fMRI and diffusion MRI studies; generalization to other modalities may require further validation.
- Optimal STC/MC order may vary with scanner hardware, subject population, and specific research question.
- Quantitative comparisons of interpolation kernels are context-dependent and may not generalize across all preprocessing steps.

Suggested Further Research

- Automated, adaptive selection of STC/MC order in high-motion or pediatric populations.
- Comparative studies of interpolation kernel effects on effective smoothness and statistical power in diverse clinical cohorts.
- Integration of real-time adaptive motion correction with deep learning–based preprocessing frameworks.

1. Introduction

Preprocessing is a critical step in neuroimaging pipelines, directly impacting the validity and interpretability of downstream analyses. Among the most debated and technically challenging steps are slice-timing correction (STC), motion correction (MC), the composition of spatial transforms for resampling, and the choice of interpolation kernels. Each of these steps addresses specific sources of temporal and spatial misalignment, but their interactions, optimal ordering, and technical implementation remain active areas of research and development. This review synthesizes current evidence and best practices, focusing on the timing and integration of STC and MC, the rationale for single-shot transform composition, and the impact of interpolation kernel selection on effective image smoothness and data quality.

Overview of Neuroimaging Preprocessing Challenges

- **Temporal misalignment**: Slices in fMRI are acquired at different times within each TR, necessitating STC to align time series across the brain.

- **Motion artifacts**: Subject motion introduces spatial misalignment and signal artifacts, requiring robust MC strategies.
- **Spatial distortions**: Susceptibility-induced distortions (SDC) and geometric misalignments between EPI and anatomical images complicate registration.
- **Interpolation effects**: Each resampling step and interpolation kernel can introduce smoothing, blurring, or aliasing, affecting statistical sensitivity and anatomical fidelity [3] [6] [12].

2. Slice-Timing Correction and Motion Correction: Timing and Integration

Optimal Timing of Slice-Timing Correction Relative to Motion Correction

- **Motion estimation should always be performed on the original, un-interpolated data**. Temporal interpolation (e.g., STC) reduces apparent motion by 10–50%, masking artifacts and biasing motion estimates [1] [2].
- **Order of STC and MC for resampling**: The optimal order is not fixed and depends on:
  - **Slice acquisition order** (sequential vs. interleaved): Segment-wise MC is beneficial for sequential acquisition, but not for interleaved [1].
  - **TR and motion level**: High motion or sub-second TRs may benefit from advanced slice-to-volume or slice-by-slice MC before STC [1] [13].
  - **Pipeline design**: Some pipelines perform MC first, then STC; others reverse the order. Both can be valid if motion estimation is always performed first [1].

Effects of STC and MC Order on Functional Connectivity Metrics

- **Functional connectivity metrics are sensitive to the order of STC and MC**. Applying STC before MC can restore signal stationarity and improve connectivity integrity, especially in sub-second TR data [1] [13] [14].
- **Temporal interpolation alters motion parameter estimates**, potentially reducing sensitivity to motion artifacts if motion is estimated after STC [2].

Influence of Slice Acquisition Order on Correction Strategies

- **Sequential acquisition**: Segment-wise MC (on slices acquired close in time) improves TSNR, especially for superior slices affected by respiratory motion [1].
- **Interleaved acquisition**: Requires specialized detection and correction methods; segment-wise MC does not confer the same benefit [1] [15].

- **Advanced MC methods**: Slice-to-volume and slice-by-slice MC are particularly advantageous for interleaved or high-motion data [12] [16].

Best Practices for Motion Estimation Timing

- **Motion estimates should be obtained prior to any temporal interpolation** (STC, outlier replacement) to preserve artifact sensitivity [2].
- **Temporal interpolation steps can mask motion artifacts**, making data appear artifact-free when it is not [2].

Synthesis: The integration of STC and MC is complex and context-dependent. The universal principle is to estimate motion before any temporal interpolation. The order of resampling (STC vs. MC) should be tailored to acquisition parameters and motion characteristics, with advanced MC methods offering improved robustness in challenging scenarios.

3. Transform Composition for Single-Shot Resampling

Principles and Evidence for Single-Shot Transform Composition

- **Composing all spatial transforms (motion, SDC, EPI → anatomy, anatomy → template) into a single resampling step** minimizes interpolation artifacts and preserves image quality [3] [4] [5].
- **Benefits**:
  - Reduces cumulative blurring from multiple interpolations.
  - Improves spatial alignment and anatomical fidelity.
  - Facilitates robust correction of motion-induced field changes and geometric distortions [4] [17].

Adaptive Weighting Schemes in Fieldmap-Based SDC

- **Adaptive weighting**: Combines fieldmap-based SDC with non-rigid registration, using confidence in fieldmap estimates to guide correction in low-confidence regions [3] [9].
- **Spatially adaptive regularization**: Bayesian and entropy-based methods allow local adaptation of registration strength, improving correction in highly distorted or low-SNR areas [18] [19].

Accuracy and Robustness of Composed Transforms

- **Simulation and empirical studies**: Show improved geometric fidelity, activation detection, and tractography accuracy when using single-shot composed transforms [5] [17] [20].
- **Deep learning approaches**: Can estimate displacement fields and perform unwarping in a single step, matching or exceeding traditional methods in speed and accuracy [21] [22].

Spatially Adaptive Regularization in Non-Rigid Registration

- **Local deformation models**: Constrain transformations to regions of distortion, reducing parameter count and avoiding implausible deformations elsewhere [10] [23].
- **Physics-based constraints**: Incorporating dephasing and field inhomogeneity models further improves correction accuracy [24] [25].

Synthesis: Single-shot transform composition is now a best practice in neuroimaging preprocessing, supported by both theoretical and empirical evidence. Adaptive and spatially regularized registration methods further enhance correction accuracy, especially in challenging regions.

4. Interpolation Kernels and Effective Smoothness

Common Interpolation Kernels in Neuroimaging

Kernel Type	Typical Use	Properties	Effects on Smoothness
Linear	Fast, basic resampling	Simple, low computational cost	Moderate smoothing, can cause jagged edges
Cubic B-spline	Standard for registration, STC	Good frequency response, smooth	More smoothing, robust, but can blur details
Wendland	Registration, norm-minimizing	Compact support, tunable	Can reduce smoothing, preserves features if support is large
Cubic Polynomial	Registration, resampling	Smoother frequency response than B-spline	Less aliasing, preserves high-frequency details
Truncated Sinc (Lanczos)	High-accuracy resampling	Good frequency properties	Minimal smoothing, computationally intensive
Kaiser-windowed Sinc	High-accuracy resampling	Adjustable window, good trade-off	Low smoothing, high fidelity

[6] [8] [26]

Comparative Effects on Effective Smoothness and High-Frequency Detail

- **Wendland kernels**: Norm-minimizing, can outperform B-splines in disease separation and feature preservation if support is adequately chosen [6].
- **Cubic polynomial kernels**: Smoother frequency response, higher PSNR, less aliasing and blurring than cubic spline [7].
- **Cubic B-spline**: Robust, but can introduce more smoothing and blur high-frequency details [26] [27].

- **Sinc-based kernels**: Best for preserving high-frequency content, but computationally demanding [8] [28].

Impacts of Temporal Interpolation on Motion Estimation and Artifact Correction

- **Temporal interpolation (STC) reduces estimated motion by 10–50%**, potentially masking artifacts and biasing downstream analyses [2].
- **Motion estimation should always precede temporal interpolation** to preserve artifact sensitivity [2].

Kernels for Minimizing Effective Smoothness and Real-Time Feasibility

- **Gaussian smoothing**: Fast, but blurs edges and textures.
- **Anisotropic/non-local diffusion**: Better preserves features, improves functional network mapping [29] [30].
- **Diffusion-informed spatial smoothing (DSS)**: Incorporates white matter orientation, enhances local connectivity [31].
- **Adaptive smoothing (deep learning)**: Modulates smoothing per volume, balances fidelity and efficiency [32].
- **Real-time feasibility**: GPU-accelerated and parallelized pipelines can achieve sub-TR processing times [33] [34].

Synthesis: Interpolation kernel choice is a critical determinant of effective smoothness and detail preservation. Wendland and cubic polynomial kernels offer advantages over cubic B-spline in many contexts, but require careful parameterization. Real-time preprocessing is feasible with modern computational resources and adaptive smoothing strategies.

5. Methodological Advances and Best Practices

Sampling Theory-Based Slice-Timing Correction Methods

- **Filter-Shift and other sampling theory–based STC methods** outperform traditional interpolation-based approaches (e.g., SPM, FSL) in temporal accuracy and robustness to motion [1] [35].
- **Effectiveness depends on scan parameters and motion levels**; optimal STC methods should be tailored to acquisition scheme [35].

Slice-to-Volume and Slice-by-Slice Motion Correction

- **Slice-by-slice prospective MC**: Reduces false positives by up to 48%, increases statistical power (26% higher peak T, 9.3-fold increase in cluster size) [11].
- **Slice-to-volume MC**: Accounts for inter-slice motion, improves activation detection and registration accuracy [12] [36].

Prospective Motion Correction: Latest Advances

- **Real-time prospective MC**: Outperforms retrospective methods, maintains signal stability, and enables detection of activation even with significant motion [37] [38].
- **Integration with tracking technologies**: Optical and deep learning–based tracking improve feasibility and accuracy [39].

Real-Time vs Retrospective Motion Correction

- **Prospective MC**: Better for intra-volume motion and spin-history effects.
- **Retrospective MC**: Handles residual artifacts; best results achieved by combining both [40] [41].
- **Hybrid and deep learning approaches**: Show promise for further improvements [42] [43].

Optimization Frameworks for Adaptive Resampling Pipelines

- **Adaptive, data-driven pipelines**: Improve temporal accuracy and reproducibility over fixed pipelines [1] [35].
- **Deep learning frameworks**: Enable real-time, adaptive smoothing and motion correction [44].
- **Standardized workflows (e.g., NiPreps, BIDS)**: Enhance reproducibility and community engagement [45].

Synthesis: Methodological advances in STC, MC, and transform composition have led to substantial improvements in data quality, statistical power, and reproducibility. Adaptive, standardized, and real-time pipelines are increasingly feasible and recommended.

6. Summary and Recommendations

Key Findings and Practical Guidelines

- **Motion estimation should always precede any temporal interpolation (STC, outlier replacement)** to avoid underestimating motion and biasing artifact detection [2].
- **The order of STC and MC for resampling should be tailored to acquisition parameters and motion characteristics**; advanced MC methods (slice-to-volume, slice-by-slice) are recommended for high-motion or interleaved acquisitions [1].
- **Composing all spatial transforms into a single resampling step is best practice** to minimize interpolation artifacts and improve spatial alignment [3] [4].
- **Wendland and cubic polynomial interpolation kernels can reduce effective smoothness and preserve high-frequency details** better than cubic B-spline, but require careful parameterization [6] [7].
- **Adaptive and spatially regularized registration methods** further enhance correction accuracy, especially in challenging regions [3] [10].

- **Real-time and deep learning–based pipelines** are increasingly feasible and offer improved robustness and reproducibility [41] [44].

Methods Text (for Reproducibility)

Slice-Timing and Motion Correction:
Motion parameters are estimated from the original, un-interpolated fMRI data using a rigid-body or slice-to-volume registration algorithm. Slice-timing correction is then applied using a sampling theory–based method (e.g., Filter-Shift) or cubic B-spline interpolation, with slice acquisition order (sequential/interleaved) specified according to the scanner protocol. For high-motion or interleaved acquisitions, advanced slice-by-slice or slice-to-volume MC is recommended prior to STC.

Transform Composition:
All spatial transforms—including motion correction, susceptibility distortion correction (SDC, using fieldmap-based or blip-up/blip-down methods), EPI-to-anatomy registration (using mutual information or B-spline non-rigid registration), and anatomy-to-template registration—are composed into a single transform. This composite transform is applied in a single resampling step using a high-fidelity interpolation kernel (e.g., Wendland, cubic polynomial, or Kaiser-windowed sinc).

Interpolation Kernels:
The choice of interpolation kernel is based on the trade-off between computational efficiency and preservation of high-frequency details. Wendland or cubic polynomial kernels are preferred for minimal smoothing and detail preservation; cubic B-spline is used for robust, general-purpose resampling; sinc-based kernels are reserved for high-accuracy applications. For real-time pipelines, GPU-accelerated implementations and adaptive smoothing methods are employed.

Quality Control:
Motion estimates, temporal SNR, and effective smoothness are monitored throughout preprocessing. Pipelines are standardized using BIDS and NiPreps frameworks to ensure reproducibility and facilitate community engagement.

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  (Full .bib and PDF references available in the referenced literature sections.)

Note: For detailed tables, methods, and bibliographic files, see the referenced literature sections [1-, *2*-, 3-, *4*-].

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