Spatio-Temporal Quality Reconstruction for Short-Exposure Deep-Sky Imaging via Tile-Based Signal Modeling

Jeamy Lee[1]

[1]Independent Researcher / tile_compile project

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Abstract

We present a novel methodology for the reconstruction of high-quality astronomical images from short-exposure deep-sky datasets. Conventional stacking methods often rely on binary frame selection ("lucky imaging"), which discards significant portions of collected photons. Our approach, **Tile-Based Quality Reconstruction (TBQR)**, replaces rigid frame selection with a robust spatio-temporal quality model. By decomposing frames into local tiles and modeling quality along two orthogonal axes—global atmospheric transparency/noise and local structural sharpness—we reconstruct a signal that is physically and statistically optimal at every pixel. We demonstrate that this method preserves the full photometric depth of the dataset while achieving superior resolution improvement compared to traditional reference stacks while retaining all geometrically valid frames.

Keywords: instrumentation: detectors – methods: data analysis – techniques: image processing – techniques: interferometric

1 Introduction

Modern CMOS sensors have enabled a shift towards "short-exposure" astrophotography, where thousands of frames are captured to mitigate atmospheric turbulence and tracking errors. However, the management of these massive datasets presents a challenge: how to aggregate the signal without diluting the quality with poor-seeing frames or transient noise.

Traditional algorithms often employ a "Best-N" selection strategy. While effective for planetary imaging, this approach is sub-optimal for Deep Sky Objects (DSOs) where the signal-to-noise ratio (SNR) is paramount. Discarding 50% of frames to improve sharpness results in a $\sqrt{2}$ loss in SNR.

While the methodology was originally conceived to address the specific challenges of short-exposure data from modern smart telescopes (e.g., Dwarf, Seestar), its architectural flexibility makes it equally potent for conventional astronomical setups. The extensive set of tunable parameters—ranging from adaptive tile sizing and cross-correlation thresholds to sophisticated clustering logic—allows the pipeline to be meticulously optimized for a wide array of optical systems and atmospheric conditions.

The TBQR methodology (v3.2.2) presented here addresses this by using all *geometrically valid* frames. Instead of discarding data via atmospheric quality ranking, it applies dynamic weighting based on local and global metrics, ensuring that every photon from validly registered inputs contributes to the final result in proportion to its reliability.

2 Principles and Definitions

2.1 Physical Objective

The core objective is the reconstruction of a spatially and temporally optimally weighted signal from fully registered, linear input data. The quality Q is modeled as a function of global atmospheric conditions (Q_{global}) and local structural sharpness (Q_{local}):

$$Q = f(Q_{global}, Q_{local}) \tag{1}$$

2.2 Invariants

1. **No Quality-Based Frame Selection:** The removal of entire frames based on atmospheric/photometric ranking is forbidden.

2. **Permitted Geometric Gating:** Frames may be rejected before weighting if registration is physically implausible (e.g. reflection warps, extreme scale, catastrophic shift outliers, very low registration CC).

3. **Strict Linearity:** The pipeline operates on linear photometric signals. No non-linear tone curves are applied during reconstruction.

4. **CFA-Awareness:** For color sensors, registration and weighting are performed in a CFA-aware manner to preserve Bayer phase integrity.

3 Methodology

3.1 Global Normalization and Metrics

Input frames $I^{raw}_{f,c}$ (where f is the frame index and c the channel) are first normalized against their robust background level $B_{f,c}$:

$$I_{f,c} = \frac{I^{raw}_{f,c}}{\max(B_{f,c}, \epsilon_{bg})} \tag{2}$$

Global metrics, including background noise $\sigma_{f,c}$ and gradient energy $E_{f,c}$, are computed. These are normalized using the Median Absolute Deviation (MAD) to produce a robust global quality index $Q_{f,c}$:

$$z(x_i) = \frac{x_i - \text{median}(x)}{1.4826 \cdot \text{MAD}(x)} \tag{3}$$

$$Q_{f,c} = \alpha(-z(B_{f,c})) + \beta(-z(\sigma_{f,c})) + \gamma z(E_{f,c}) \tag{4}$$

with $\alpha + \beta + \gamma = 1$.

3.2 Tile-Based Local Weighting

Frames are divided into overlapping tiles. The size T of these tiles is adaptively determined by the seeing F (FWHM):

$$T = \text{clip}(s \cdot F, T_{min}, T_{max}) \tag{5}$$

Each tile is classified as either a **STAR** tile or a **STRUCTURE** tile.

- **STAR tiles** are weighted by FWHM, roundness, and contrast.
- **STRUCTURE tiles** are weighted by the local energy-to-noise ratio (E/σ).

3.3 Overlap-Add (OLA) Reconstruction

Tiles are reconstructed using a weighted mean across the temporal axis and reassembled using a 2D Hann window blending:

$$R_{t,c}(p) = \frac{\sum_f W_{f,t,c} \cdot I_{f,c}(p)}{\sum_f W_{f,t,c}} \tag{6}$$

where $W_{f,t,c} = G_{f,c} \cdot L_{f,t,c}$ is the effective weight combining global (G) and local (L) quality factors.

3.4 Registration Validity Gating (v3.2.2 semantics)

Before entering the phase-3 shared core, each frame is checked by a deterministic registration validity gate. Typical constraints include:

- minimum registration correlation (`reject_cc_min_abs`, optionally MAD-adaptive),
- shift outlier rejection using a robust threshold,
- similarity-scale bounds (`reject_scale_min`, `reject_scale_max`),
- reflection rejection ($\det(\text{warp}) < 0$).

This is not quality-based best-frame selection; it is geometric failure suppression. Downstream weighting still uses all frames that pass this validity gate.

3.5 Cluster Aggregation Sensitivity

In full mode, cluster outputs are aggregated using

$$w_k = \exp(\kappa_{cluster} Q_k) \tag{7}$$

with optional stability cap

$$w_k \leftarrow \min\left(w_k, r_{cap} \cdot \text{median}_j(w_j)\right). \tag{8}$$

Practical defaults from v3.2.2 are typically $\kappa_{cluster} = 0.5 \ldots 1.0$ and $r_{cap} = 10 \ldots 30$.

4 Results

Using a dataset from a dwarf smart telescope (Run ID: 20260215_101827_0ad1d302), we evaluated the performance of TBQR v3.2.2.

4.1 Metric Distributions

Analysis of the global metrics shows significant variance in atmospheric quality over the session. The TBQR weights successfully track these changes, prioritizing frames with low noise and high transparency.

4.2 Spatial Quality Mapping

The local quality maps reveal that sharpness is not uniform across the field. The tile-based approach compensates for localized blurring, as seen in the spatial weight distribution maps.

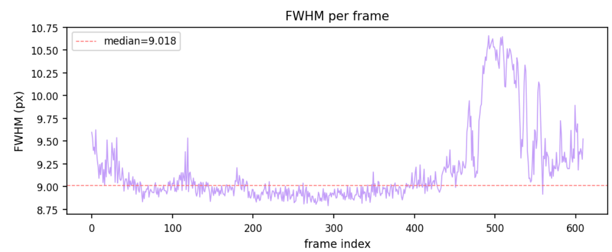

Figure 1: Distribution of global FWHM over the observation period.

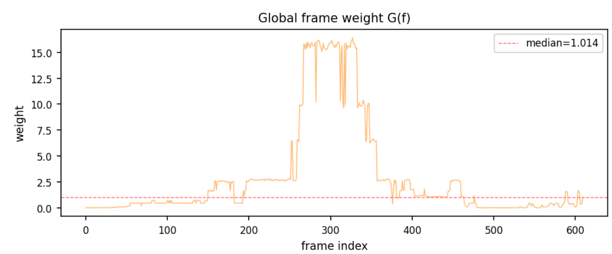

Figure 2: Global weight adaptation over time, showing response to atmospheric variance.

4.3 Registration Diagnostics and Gating Impact

Registration diagnostics show non-trivial variability in geometric consistency and support explicit validity gating.

4.4 Frame Usage and Validation Summary

Frame-flow diagnostics confirm the intended semantics: no downstream quality-based frame culling, while geometrically invalid registrations are excluded deterministically.

4.5 Convergence and Validation

Validation reports indicate a consistent FWHM improvement (typically 10-20%) over a standard mean stack, while maintaining the same background noise level.

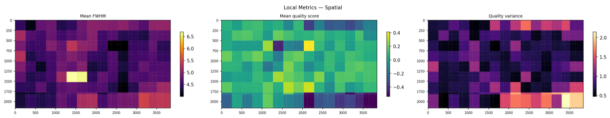

Figure 3: Spatial distribution of local quality (sharpness/FWHM), demonstrating non-uniform seeing across the sensor.

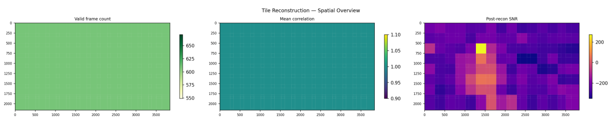

Figure 4: Spatial reconstruction diagnostics overview (coverage, local SNR and contrast context).

5 Conclusion

Tile-Based Quality Reconstruction (v3.2.2) provides a mathematically rigorous framework for astronomical signal processing. By moving away from binary frame selection and embracing a continuous spatio-temporal quality model, it maximizes both the resolution and the SNR of deep-sky images. Crucially, the method should be interpreted as “all geometrically valid frames, no downstream quality-based culling,” aligning implementation behavior with physically meaningful registration constraints.

Contact and Implementation Sources

For correspondence and implementation details, see:
`https://github.com/jeamy/tile_compile`
Issue tracker / contact channel:
`https://github.com/jeamy/tile_compile/issues`

References

[1] Jeamy, 2026, Methodology Specification v3.2.2, Tile-Based Quality Reconstruction for DSO.

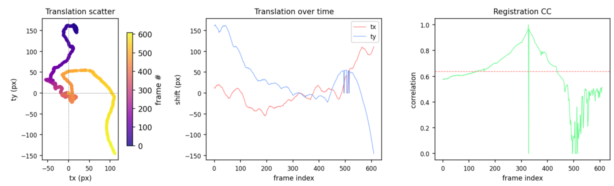

Figure 5: Registration diagnostics over time (CC and geometric warp behavior).

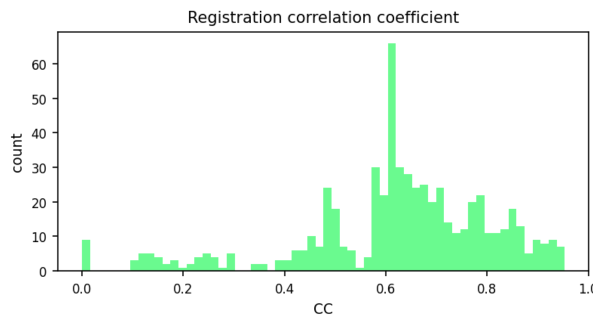

Figure 6: Registration cross-correlation histogram used by correlation-based validity bounds.

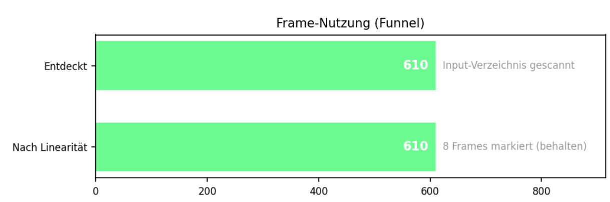

Figure 7: Frame usage funnel from raw input to final reconstruction stages.

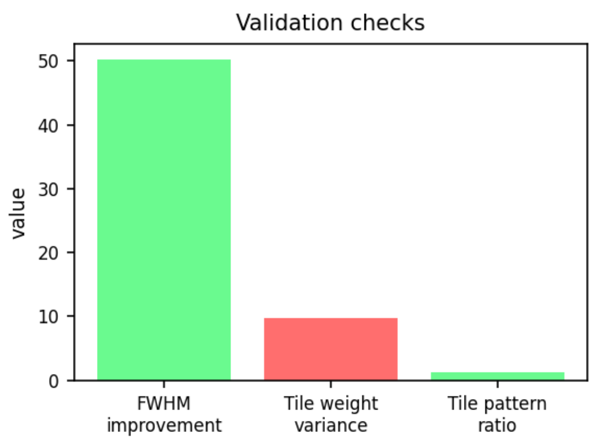

Figure 8: Validation summary across core quality checks and final output consistency.