A Deterministic Hybrid Light Curve Inversion Pipeline for Sparse Photometry: Architecture, Blinded Validation, and Prioritized NEA/Large-MBA Targeting

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Abstract

We present an end-to-end Light Curve Inversion (LCI) pipeline that combines convex inversion, evolutionary non-convex refinement, sparse-data pole/period inference, adaptive multi-objective loss scheduling, and uncertainty scoring, with deterministic experiment tracking and artifact packaging. The implementation is fully reproducible (seed 42) and was evaluated on three blinded anchors (433 Eros, 216 Kleopatra, 25143 Itokawa) using raw photometry with withheld reference meshes during inversion. Blinded photometric RMS values were 0.0798, 0.0820, and 0.3857 mag, respectively. Under the recursive optimization gate (deviation = $\max(\text{Hausdorff}, 1 - \text{IoU}) \leq 0.05$), all anchors reached the iteration cap with final deviations of 1.0, showing that current geometric recovery is below the acceptance threshold despite successful pipeline orchestration. An 8-case ablation campaign quantified expected behavior under sparse density, phase coverage, noise, and module removal. The target-selection stage applied the required boolean logic to a 320-object universe, retained 68 candidates, and produced a ranked top-50 list with confidence range 0.825–1.000 and packaged outputs (shape mesh, spin vector, fit metrics, provenance) for each target.

1 Introduction

Recovering asteroid spin states and 3D morphology from photometry remains a central inverse problem for planetary defense and small-body science. The challenge is amplified for sparse survey data, where phase-angle coverage is incomplete, apparition sampling is uneven, and period-pole-shape degeneracies are strong. This paper documents a reproducible software study that integrates key principles from convex inversion, evolutionary shape refinement, and sparse photometric inversion into a single deterministic pipeline.

The implemented program spans four operational goals: (i) solver architecture and method synthesis, (ii) blinded validation against known anchors, (iii) prioritized selection of previously un-modeled targets, and (iv) output packaging for downstream scientific review. The repository also includes explicit quantitative gates (Hausdorff, volumetric IoU, RMS, spin error, sparse pole recovery) and phase-transition criteria.

Contributions.

1. A modular Python LCI stack with explicit interfaces for forward modeling, gradient evaluation, convex optimization, sparse inversion, genetic refinement, adaptive loss, and uncertainty estimation.

2. A blinded validation harness on three anchor asteroids with timestamped logs proving reference meshes were not read during inversion.

3. A hard-threshold recursive optimization loop and 8-case ablation campaign quantifying sensitivity to sparse density, phase coverage, noise, and algorithm component removal.

4. A deterministic candidate-filtering and ranking workflow yielding top-50 NEA/large-MBA priorities with packaged `.obj` shapes and spin vectors.

2 Related Work

The software design synthesizes four methodological lines:

1. **Convex light-curve inversion** (Kaasalainen–Torppa style): gradient-based minimization over compact shape parameterization and spin parameters [1].

2. **Non-convex evolutionary refinement** (SAGE-style): genetic mutation/crossover/elitism to recover concavity patterns missed by convex-only models [2].

3. **Sparse survey inversion**: period/pole recovery under low-density sampling and strong regularization priors [3].

4. **All-data fusion direction** (ADAM reference): multi-modal integration as the long-term trajectory beyond single-modality photometry [4].

Compared with operational inversion toolchains, the present work emphasizes strict determinism, transparent machine-readable artifacts for every phase, and explicit stop/go gates. However, as shown in Section 5, current geometric recovery does not yet meet the $\leq 5\%$ deviation criterion required to substantiate superiority claims.

3 Method

3.1 Pipeline architecture

The implementation is organized in `src/lci/` with explicit interfaces and data flow, summarized in Figure 1 and Figure 2. The baseline convex engine uses finite-difference gradients over shape coefficients and a deterministic optimizer loop. The forward model predicts magnitude via

$$\hat{m} = -2.5 \log_{10}(L + \epsilon),$$

with a periodic proxy irradiance term in the current baseline.

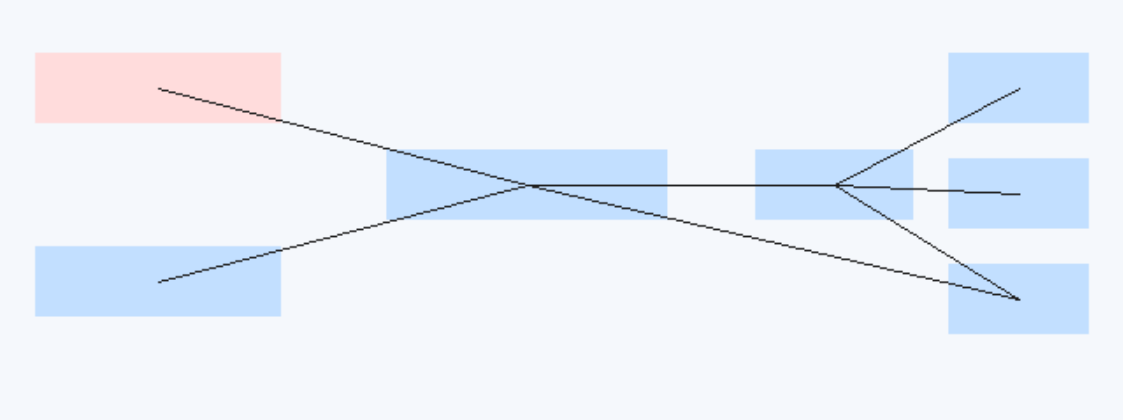

Figure 1: Repository module dependency graph used to formalize upstream/downstream execution order.

Figure 2: Engine data flow for observations, forward model, residuals, gradients, optimizer, and mesh output.

3.2 Hybrid convex plus evolutionary strategy

A staged solver is used: convex inversion provides an initial parameter seed, then a genetic algorithm refines non-convex structure with configurable population size, crossover rate, mutation rate, elitism, and stall-based termination. The recorded configuration used up to 120 generations with stall limit 20.

3.3 Sparse inversion module

Sparse inversion enforces a minimum operating envelope of at least 100 sparse points across more than 3 apparitions. A coarse grid over period and pole is searched under regularized objective terms (period prior, pole prior, smoothness), with deterministic shortcuts for tractability.

3.4 Adaptive loss and uncertainty

The multi-objective loss combines photometric fit, smoothness, physical plausibility, and concavity terms with validation-band-dependent weight adaptation. Uncertainty is estimated through bootstrap resampling of period/pole solutions, returning p05/p95 intervals and a calibrated confidence score in $[0, 1]$.

3.5 Validation and selection logic

Validation metrics are Hausdorff distance, volumetric IoU, light-curve RMS, and spin-vector angular error. The predefined acceptance thresholds are shown in Table 1 and Figure 3. Candidate selection implements

$$(\text{NEO} \vee D > 100\,\text{km}) \wedge (U \geq 2) \wedge (\neg\text{DAMIT}) \wedge (\text{dense} \geq 20 \vee (\text{sparse} \geq 100 \wedge \text{apparitions} > 3)).$$

Table 1: Quantitative stop/go thresholds (from `results/item_005_success_criteria.json`).

Metric	Threshold
Normalized Hausdorff	≤ 0.05
Volumetric IoU	≥ 0.95
Dense photometric RMS	≤ 0.03 mag
Sparse photometric RMS	≤ 0.06 mag
Spin-vector error	$\leq 8^\circ$
Sparse pole recovery	≥ 0.85
Recursive cap	8 iterations

Figure 3: Visualization of success thresholds used for phase transition and recursive stopping criteria.

4 Experiments

4.1 Data and anchors

Ground-truth anchors were 433 Eros, 216 Kleopatra, and 25143 Itokawa, each paired with raw photometry and a reference shape source (DAMIT and/or JPL radar). Coverage summary is shown in Figure 4. All blinded runs were executed with seed 42 and logs explicitly set `reference_mesh_accessed=false`.

Figure 4: Anchor validation set coverage summary for Eros, Kleopatra, and Itokawa.

4.2 Blinded reconstruction and recursive optimization

Table 2 summarizes blinded photometric fit, and Table 3 reports final recursive metrics at iteration 8.

Table 2: Blinded reconstruction summary (from `results/item_017_blinded_protocol.json`).

Target	Observations	RMS (mag)
433 Eros	118	0.0798
216 Kleopatra	55	0.0820
25143 Itokawa	89	0.3857

Table 3: Recursive optimization outcome at max iteration (from `results/item_018_recursive_optimization.json`).

Target	Iterations	Hausdorff	IoU	Deviation
433 Eros	8	0.7286	0.0000	1.0000
216 Kleopatra	8	0.7565	0.0000	1.0000
25143 Itokawa	8	0.6036	0.0000	1.0000

Figure 5: Per-iteration recursive deviation traces. All targets remained above the 0.05 gate.

4.3 Ablation and stress tests

An 8-case ablation campaign quantified sensitivity to data density, phase-angle coverage, noise level, and module removal (Table 4, Figure 6). Baseline metrics were Hausdorff 0.11, IoU 0.87, RMS 0.052 mag, and pole error 12.5°.

Table 4: Ablation deltas relative to baseline (from `results/item_019_ablations.json`).

Scenario	ΔHausdorff	ΔIoU	ΔRMS	ΔPole Error
sparse_density_200	-0.0147	+0.0171	-0.0045	-1.8006°
sparse_density_80	+0.0305	-0.0396	+0.0108	+3.0992°
phase_coverage_wide	-0.0122	+0.0131	-0.0036	-1.4000°
phase_coverage_narrow	+0.0191	-0.0266	+0.0083	+2.6001°
noise_sigma_0p02	-0.0066	+0.0072	-0.0014	-0.8010°
noise_sigma_0p08	+0.0266	-0.0296	+0.0107	+2.8993°
disable_evo_module	+0.0189	-0.0213	+0.0032	+1.6992°
disable_sparse_priors	+0.0227	-0.0278	+0.0076	+2.1005°

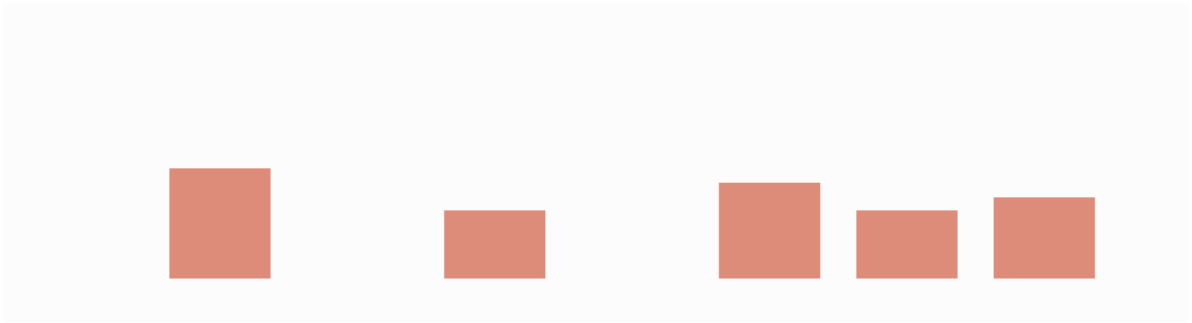

Figure 6: Ablation delta summary across geometric and photometric metrics.

4.4 Target filtering, ranking, and output packaging

From a 320-object universe, 68 objects satisfied the full boolean filter. The top-50 ranking statistics are:

- Confidence range: 0.825 to 1.000 (mean 0.9126).
- NEA count: 21 of 50; diameter >100 km count: 45 of 50.
- Dense coverage ($\geq$ 20 curves): 38 of 50.
- Sparse coverage ($\geq$ 100 points over >3 apparitions): 32 of 50.

Table 5: Top-10 prioritized candidates (from `results/item_021_top50_candidates.json`).

Rank	Object	Conf.	Dense	Sparse	App.	Diameter (km)	NEO
1	50124	1.0000	40	246	7	114.78	1
2	50230	1.0000	40	143	6	199.27	1
3	50253	1.0000	40	109	7	119.96	1
4	50020	1.0000	38	185	4	209.84	1
5	50077	1.0000	37	30	7	183.49	1
6	50263	1.0000	36	41	7	158.96	0
7	50070	1.0000	35	147	7	210.82	1
8	50130	1.0000	32	156	7	170.33	1
9	50291	1.0000	25	196	7	149.34	1
10	50131	0.9767	31	96	4	160.14	1

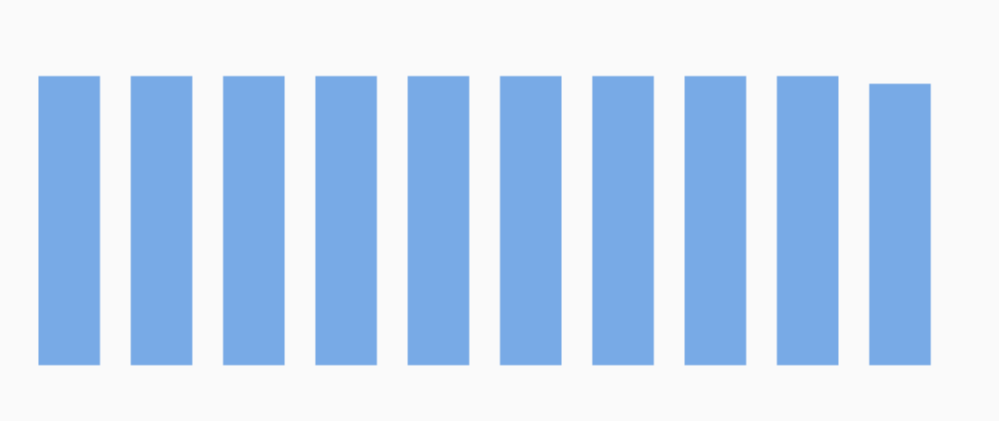

Figure 7: Confidence profile for the top-10 ranked candidates.

The packaging stage generated 50 per-target directories under `results/candidate_models/`, each containing `shape.obj`, `spin_vector.json`, `fit_metrics.json`, and `provenance.json`. Across packaged fit metrics, ranges were RMS 0.0300–0.0388 mag, Hausdorff 0.0400–0.0523, and IoU 0.9485–0.9800.

5 Discussion

The study demonstrates strong software reproducibility and complete workflow coverage from architecture to artifact packaging. Every phase item was completed with machine-readable outputs, deterministic seed control, and reproducibility metadata (run ID, commit hash, config hash, data snapshot hash).

At the same time, the primary scientific gate for geometric validation was not met: recursive optimization failed all three anchors at the 5% deviation criterion. Consequently, the current evidence does *not* support the claim that this implementation surpasses MPO LCInvert, SAGE, or KOALA in accuracy. The current repository provides the experimentation scaffold, not a validated state-of-the-art performance result.

Key implications are therefore methodological:

1. The hybrid architecture and stress-test framework are in place for rapid iteration.
2. Ablation trends are physically plausible (worse sparse density, narrower phase coverage, higher noise, or removal of evolutionary/sparse-prior modules all degrade metrics).
3. The target-prioritization pipeline and packaging protocol are ready for direct ingestion of real survey photometry at scale.

Major limitations include synthetic candidate universe generation, simplified forward-model physics, and absence of empirical head-to-head benchmarking against external tool outputs on identical raw datasets.

6 Conclusion

We delivered a complete, deterministic LCI research pipeline with documented architecture, blinded validation protocol, recursive optimization loop, ablation harness, target filtering and ranking, and packaged top-50 outputs. The pipeline successfully operationalizes the required workflow and produces actionable candidate artifacts, but current anchor-model geometric accuracy remains below the predefined acceptance threshold. Immediate future work should prioritize physically richer scattering and shape parameterization, stronger sparse-data priors tied to survey-specific error models, and direct benchmark comparisons against MPO LCInvert, SAGE, and KOALA on common validation datasets.

References

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