



# WorldTrace

## Addressable Memory for Video World Models

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Project page

### Motivation

Autoregressive video world models promise interactive worlds - but **visual persistence** collapses once generation exceeds the training horizon.

Can an autoregressive video world model reliably remember where it has been, at any generation length?

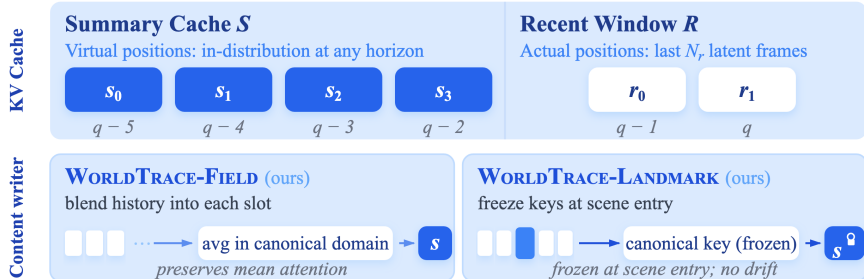
#### Position and Content are Two Coupled Bottlenecks

① **Addressability:** Temporal RoPE offsets exceed the training range, making cached memories unreadable even when physically present.

② **Content Fidelity:** Naive key averaging in RoPE-rotated space causes phase cancellation, destroying the signal that compressed summaries should carry.

### Method: WorldTrace

#### WorldTrace



#### Slot-Rank Position Assignment

Virtual position for summary slot  $s$ :

$$t_s^v = q - (L_{\text{attn}} - 1 - s), \quad s = 0, \dots, N_s - 1$$

$q$  = current query ·  $L_{\text{attn}} = N_s + N_r$  = local attention window (latent frames) ·  $s$  = slot rank from oldest

**In-distribution** at any generation length

**Horizon-stable:** rank-only offsets

#### WorldTrace-Field

Averages *all* history into each summary slot in the **canonical (unrotated) key domain**, then re-rotates to the slot's virtual position.

$$K_{\text{field}}^f(t^v) = R(\theta_f t^v) \frac{1}{M} \sum_{m=1}^M R(-\theta_f t_m) K_{t_m}^f$$

Avoids phase cancellation by aligning keys to a shared canonical phase. **Goal:** coherence: drift-free generation at long horizons.

#### WorldTrace-Landmark

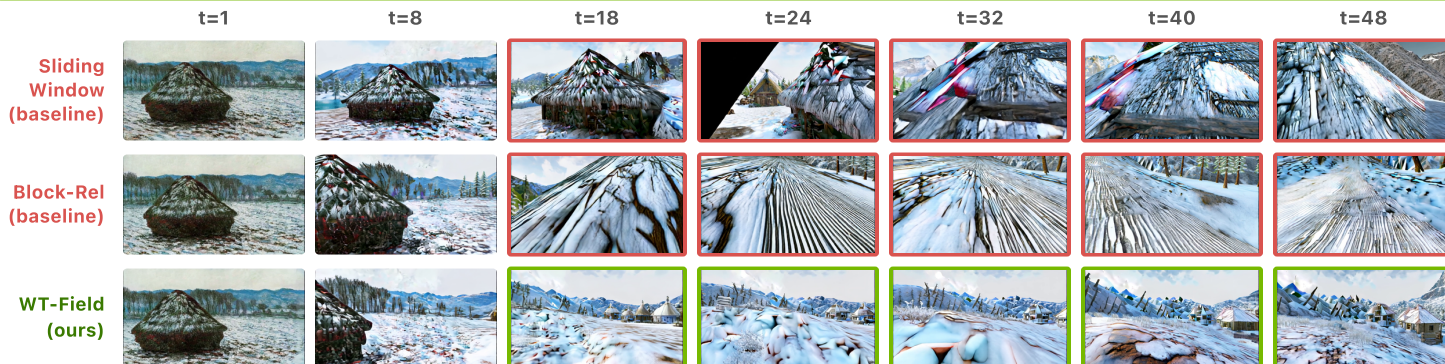
Detects scene-entry events via cosine-distance spikes in canonical-K space. Fills summary slots with **verbatim frames** at detected boundaries, frozen in canonical form.

$$K_{\text{land}}^f(t_s^v) = R(\theta_f t_s^v) R(-\theta_f t_{\ell^*}) K_{t_{\ell^*}}^f$$

Key stored once at landmark time; single rotation per shift; no float error accumulation. **Goal:** episodic recall after a long detour.

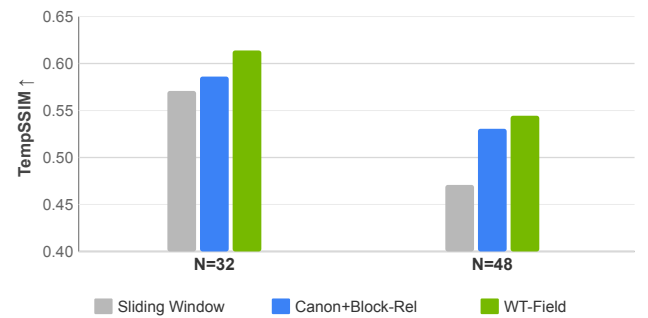
### Experiments

#### WorldTrace-Field



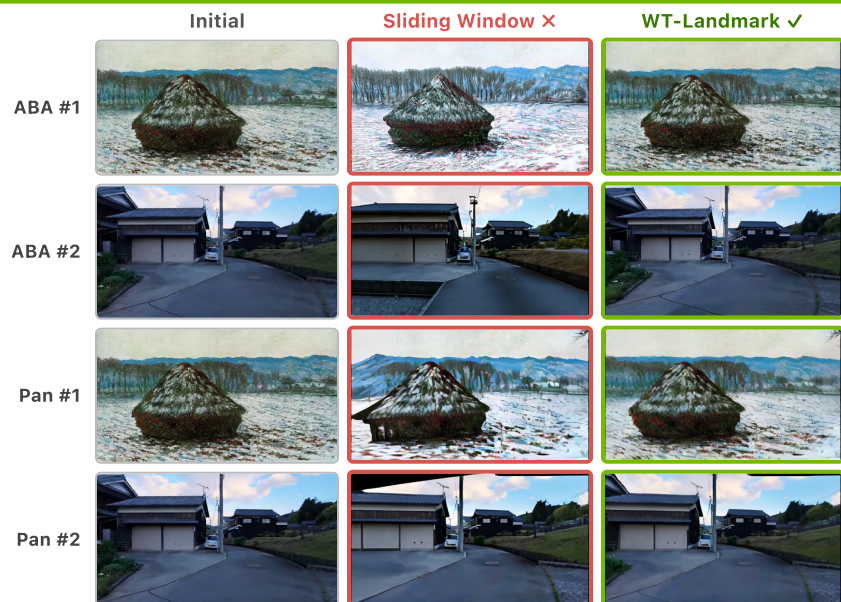
Both baselines (Sliding Window, Block-Rel) diverge from  $t=18$  ✗; WT-Field remains coherent through  $t=48$  ✓.

#### Coherence: TempSSIM ↑



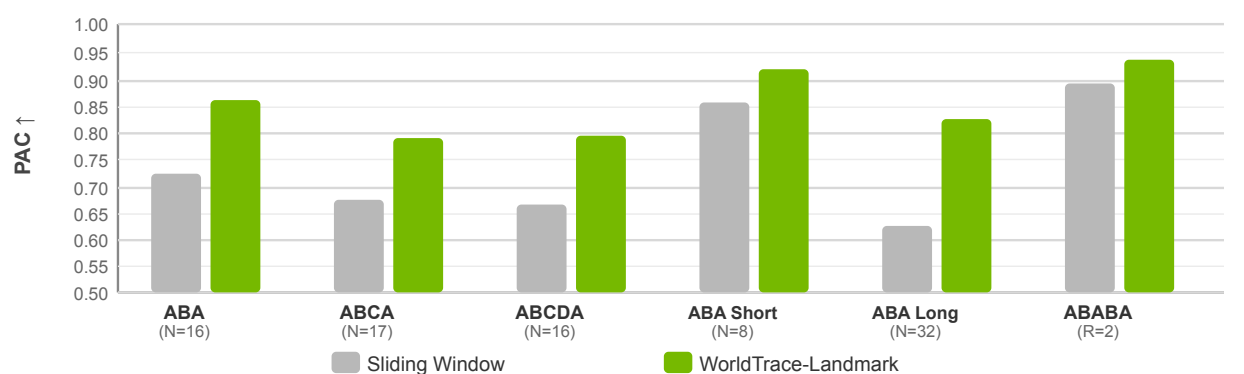
+15.5% relative TempSSIM at  $N=48$ ; WT-Field leads on both horizons.

#### WorldTrace-Landmark



WT-Landmark faithfully restores scene A across diverse environments.

#### LoopBench PAC ↑ — Sliding Window vs. WT-Landmark



Gap widens with context distance (+6.3% to +19.8%). Consistent gains across revisit depth.

### Conclusion

**Long-horizon failure is fundamentally a problem of addressability.**

#### OOD Positions Are the Binding Constraint

Content compression alone cannot restore recall once temporal RoPE offsets go out-of-distribution.

#### WT-Field +15.5% TempSSIM

Canonical key averaging improves long-range coherence at 24× generation horizon.

#### Training-Free

Only the KV cache changes: no fine-tuning, no model modification. Applies to any temporal-RoPE AR video model.

#### WT-Landmark +19.3–20.0% PAC

Frozen canonical landmark keys restore episodic recall across all LoopBench topologies.