

Identity Through Interruption: A Motion-Signature-First Decision Architecture for Multi-Object Re-Identification

Anonymous

Abstract—Appearance-based person re-identification fails exactly where identity matters most: visually identical targets, occlusion, and re-entry leave appearance embeddings uninformative or misleading. We present an identity architecture in which motion is the primary signal: an online, forward-only decision layer grows bounded uncertainty regions around missing targets, stages gate–verify–bind decisions that hold hypotheses rather than guess under ambiguity, and tracks co-located identity groups through pile-ups without re-spawning them. On synthetic hard segments the system sustains statistically zero identity switches (IDSW) across 20 seeds—including an appearance-free ballistic target—where appearance-first baselines show up to $30\times$ more. On MOT17 (all seven train sequences), the pose-free group-level mechanism cuts identity switches by 21% ($1,265 \rightarrow 995$) and raises hard-IDF1 from 0.300 to 0.324. Under a real low-recall detector, a velocity-consistency re-acquisition gate closes the IDF1 gap to SORT to 0.7pp on the most stress-affected sequence, and a generalizable channel-calibration audit flags the appearance channels of two independent trackers as net-harmful at operating scale.

Index Terms—multi-object tracking, re-identification, decision architecture, hypothesis-holding, gait, channel calibration

I. INTRODUCTION

Multi-object tracking (MOT) and re-identification are conventionally coupled through appearance. DeepSORT [2], the dominant lineage, gates identity by nearest-neighbor distance in an appearance embedding space, and modern trackers such as ByteTrack [3], OC-SORT [4], BoT-SORT [5], and StrongSORT [6] refine association on the same detection stream. This coupling has a structural blind spot: appearance is informative only when it is discriminative. Two pedestrians in identical uniforms, a person occluded behind a pillar, a target exiting and re-entering a frame, or an object with no stable appearance at all (a ball) are precisely the cases where the embedding cannot separate identities or actively misleads the association. Gait recognition has matured as a cross-view recognition problem [7], [8], and skeleton-based embeddings [9] are well studied, but their use inside online, noisy, single-camera tracking remains underexplored. Decision-theoretic trackers (MHT [13], JPDA [14]) maintain identity hypotheses but commit or marginalize rather than hold candidates open with bounded memory under an explicit no-guess policy.

We take the complementary position: *identity is a decision problem, and motion is a first-class identity signal*. A person’s gait, and any target’s characteristic motion style, are intrinsic to the identity in a way that pixels are not: they survive occlusion, are invariant to clothing, and persist across re-entry.

We contribute an online, forward-only architecture with (i) a staged decision layer that *holds hypotheses* under ambiguity (disabling it multiplies dense-scene identity switches $\sim 5.7\times$); (ii) predictive *ghosts* with bounded, growing uncertainty and a continuous *belief stream* that makes identity continuity a measurable path property (zero interruptions, zero teleports); (iii) gait and trajectory-style motion signatures with appearance demoted to a supporting gate; (iv) group-level pile-up tracking that needs no pose and transfers to real data; and (v) a channel-calibration audit that flags uncalibrated appearance channels as net-harmful. Every number is verified against the released evaluation harness; a detector-recall audit reports the floor we cannot escape rather than hide it.

II. METHOD

A. Architecture and decision layer

The system is a two-loop online architecture (Fig. 1). A high-frequency loop runs every frame: a SORT-lineage fast tracker maintains short-term temporary tracks (explicitly *not* identity), while each persistent ID’s ghost is predicted forward with growing uncertainty. A low-frequency loop accumulates a rolling pose buffer per temporary track; once enough frames exist, the buffer becomes the *probe* compared against stored gait signatures. Both loops feed the decision layer, which routes each observation through a staged test and either binds it to an existing persistent ID, spawns a new one, or holds a set of hypotheses. The output has two streams: the *observation stream* (boxes from current detections, MOT-comparable) and the *belief stream* (a continuous predicted trajectory for every non-parked ID, every frame).

For each observation the layer applies in order: **(1) Gate**—is the box inside the predicted growing-uncertainty region of an existing ID’s ghost? The gate radius is $\text{base} + \text{growth} \times \text{frames_missing}$, capped at the disk reachable at the speed ceiling before the target is declared ghosted. **(2) Structural**—relative height tolerance 30% and an absolute aspect band (0.08–1.15), rejecting merged blobs and degenerate boxes. **(3) Motion-signature**—only with ≥ 2 candidates and a pose probe: gait similarity fused with ghost-nearness geometry and a small trajectory-style bonus. **(4) Bind or spawn or hold**—bind if the fused score clears 0.80 and beats the runner-up by 0.10; otherwise, if hypotheses are held, keep the ambiguous set open up to 32 frames; a single structurally-failing gated detection spawns a fresh ID; ≥ 2 gated members under one box is a pile-up $\rightarrow$ hold, never invent an ID. Appearance is

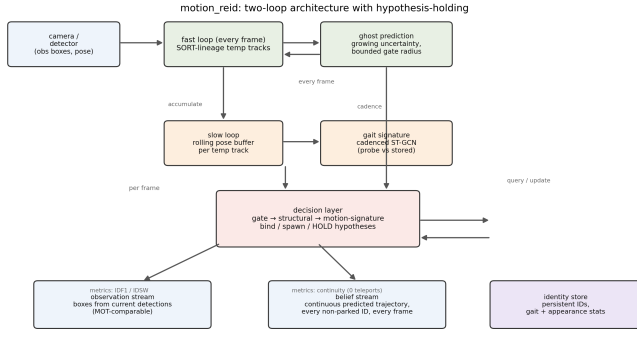


Fig. 1. Two-loop architecture: detection → fast loop (temp tracks + ghost prediction) → slow loop (pose buffers, cadenced ST-GCN signatures) → decision layer (gate → structural → motion-signature bind / spawn, with hypothesis-holding) → observation and belief streams.

applied only as a non-emptying prune of the candidate set ($\text{appearance_min} = 0.6$).

B. Ghosts, belief, and the velocity gate

Each person ID owns a per-target motion model that predicts forward with velocity decay while unobserved, edge-parks at the exit zone when a target leaves toward the frame edge, and grows its uncertainty at the target’s measured speed ceiling. The belief stream emits a box every frame: the observed box when bound, the ghost prediction while hidden, with the center EMA-smoothed ($\alpha = 0.6$) so re-acquisition eases in instead of snapping.

Under a stressed detector a missed target’s uncertainty disk can contain an unrelated pedestrian; proximity alone then re-binds the wrong identity (a switch). For a *ghosted* ID, the re-acquisition path additionally requires the displacement from the ghost’s prediction to the detection to point along the ghost’s predicted velocity; otherwise the layer holds until motion evidence resolves the candidate. The velocity gate is scoped for stress: OFF by default (preserving every synthetic number), ON for deployment under low-recall detectors.

C. Motion signatures

Gait is an ST-GCN embedding (14 joints, spatial-temporal graph convolution) trained with triplet loss on 480 synthetic identities—uniform-blind. Per ID, a rolling pose buffer accumulates; every 8 frames, windows of 32 frames are embedded and appended to the ID’s signature memory (bounded at 24). A re-entrant ID’s fresh buffer is the probe compared (cosine) against stored signatures; candidates without a signature score exactly 0. Trajectory style: from the bound-center history the layer accumulates per-ID mean speed, dominant heading (circular mean), and turning energy; the motion-style match is fused into the bind score at weight 0.10 and requires ≥ 16 observed frames.

D. Group-level pile-up tracking

When one observation carries several co-located member identities (a merged pile blob), per-frame identity resolution

is impossible; the system tracks the *group*: the blob carries the members through the merge (every member stays alive, no spawn cascade on split), and emerging identities re-bind on split by velocity-direction agreement plus proximity. The mechanism needs no pose and therefore also operates on the real MOT17 runs, where it is the only identity channel that does not depend on pose availability.

III. EXPERIMENTS

A. Protocol

Synthetic hard segments. Seven scenarios (300–420 frames) rendered through a detector emulator that injects realistic failure modes: identical-uniform twins crossing; a walker behind a pillar; out-of-frame re-entry at a different position; a ball behind a pillar mid-flight; four identical walkers merging into one blob; six identical walkers with repeated merges; and a control with differently colored walkers. The hard segment of each scenario is the exact frame range containing the interruption; metrics are computed on hard segments only unless stated. Trackers: motion_reid vs. SORT [1], DeepSORT [2], ByteTrack [3], all on identical detection streams, 20 seeds. Paired Wilcoxon signed-rank tests, Holm-corrected.

MOT17. Standard public-detection protocol: FRCNN boxes, counted pedestrians only, each sequence rescaled so the median pedestrian height is 100 px—a fixed global scale applied identically to every tracker. Two transfer constants are data-derived globally (gate growth 8.0 px/frame, speed ceiling 12.0 px/frame); leave-one-out re-derivation per fold leaves the conclusions unchanged. Metrics via motmetrics [10] (following CLEAR MOT [15]) and HOTA [11].

B. Synthetic results: zero switches where appearance breaks

Table I reports hard-segment IDF1/IDSW (mean over 20 seeds). motion_reid and DeepSORT are the only trackers that stay at (statistically) zero IDSW through every interruption: 0 switches in 20/20 seeds on re-entry, the ballistic ball, and the identical-twin crossing, and exactly one switch in a single seed on occlusion—while SORT and ByteTrack switch on occlusion in every seed (means 3.2 and 2.8). The ball is the cleanest statement of the thesis: an object with no usable appearance, re-bound purely by physics-trajectory prediction (IDF1 0.817 vs. 0.668 best appearance baseline). The losses are as honest as the wins: DeepSORT wins IDF1 on occlusion, reentry, and the distinct control by leaning on color, exactly where appearance is informative; in dense/pileup scenes hypothesis-holding costs IDF1 (0.467/0.430 vs. 0.547/0.605) in exchange for far fewer switches (14.9/5.2 vs. 19.9/7.8).

After Holm correction, motion_reid beats or matches each baseline on 12/21 IDF1 and 7/21 IDSW comparisons; the mechanism claims are individually significant (hypothesis-holding dense IDSW $p_{\text{holm}} = 4 \times 10^{-4}$; appearance removal distinct IDF1 $p_{\text{holm}} = 0.008$; zero-switch crossing $p_{\text{holm}} = 0.013$; pile-up cluster gain $p = 0.085$).

TABLE I
HARD-SEGMENT IDF1/IDSW, 7 SCENARIOS $\times$ 20 SEEDS (MEAN). BEST
PER ROW BOLD.

scenario	motion_reid	SORT	DeepSORT	ByteTrack
crossing (twins)	0.929/0.0	0.893/0.7	0.927/0.2	0.940/0.1
occlusion	0.924/0.1	0.321/3.2	0.937/0.1	0.330/2.8
reentry	0.912/0.0	0.904/0.1	0.951/0.0	0.904/0.1
ball	0.817/0.0	0.487/3.9	0.643/0.0	0.668/0.5
dense	0.467/ 14.9	0.393/40.2	0.547/19.9	0.425/34.9
pileup	0.430/ 5.2	0.557/7.0	0.605/7.8	0.574/6.9
distinct (control)	0.678/10.3	0.605/12.0	0.824/2.8	0.627/12.1

C. Ablations

Removing exactly one subsystem at a time: **hypothesis-holding** is the load-bearing mechanism—off, dense IDSW explodes 14.9 $\rightarrow$ 84.4, pileup 5.2 $\rightarrow$ 17.4, distinct 10.3 $\rightarrow$ 19.6, at a stated cost (higher raw IDF1 in pileup/distinct, lower in dense). **Gait and appearance are contributors, not oracles**: removing gait leaves crossing IDF1 *higher* (0.929 $\rightarrow$ 0.951)—synthetically geometry suffices wherever pose could help; removing appearance collapses the distinct control (0.678 $\rightarrow$ 0.578) and changes nothing on identical-uniform scenarios. **Group-level pile-up tracking** raises pile-up hard IDF1 by +4.5 pp (0.385 $\rightarrow$ 0.430) at a small switch cost, and its decisive evidence is the real-data run below.

D. MOT17: the mechanism transfers, the uncalibrated channels do not

With gait and appearance dormant, the geometry-only system loses to every modern tracker on absolute IDF1 (mean hard-IDF1 0.333 vs. 0.493–0.522; full per-sequence table in the supplementary material)—the honest ceiling of a pure-geometry gate on real footage. Leave-one-out re-derivation of the two transfer constants gives mean hard-IDF1 0.287 ± 0.063 with 534 IDSW vs. 0.333/533 fixed: the same ceiling, the same ordering.

With FRCNN boxes + YOLOv8-pose keypoints + ImageNet-pretrained MobileNet-v3 embeddings [12] (DeepSORT receives the same embeddings; Table II), two findings dominate. **The cluster mechanism works on real data without pose**: it cuts identity switches **1,265 $\rightarrow$ 995** (–21.3%) and raises hard-IDF1 0.300 $\rightarrow$ 0.324, with the largest effects on the crowded group-walking sequences (MOT17-04 393 $\rightarrow$ 206, –47.6%; MOT17-11 213 $\rightarrow$ 149, –30.0%); the paired per-sequence test is consistent but underpowered at $n = 7$ ($p = 0.156$). **The appearance channel is anti-informative at operating scale**: MobileNet-v3 embeddings on ~ 34 px crops reject true binds, and each rejected bind is a spawn—removing the channel removes 463 of 995 switches (47%) and IDF1 *risers* (0.324 $\rightarrow$ 0.332; paired $p = 0.031$). The same embeddings degrade DeepSORT identically (mean hard-IDF1 0.522 $\rightarrow$ 0.458, six of seven sequences): the finding is about channel *calibration*, not about our system. The belief stream reports zero interruptions/teleports on all seven real sequences in every variant.

TABLE II
HYBRID MOT17, 7 SEQUENCES, HARD-SEGMENT TOTALS.

run	IDF1	IDSW	interpretation
full	0.324	995	both channels + clusters
–gait	0.322	1,039	pose coverage 0–41%
– appearance	0.332	532	uncalibrated gate $\rightarrow \approx 47\%$ of switches
–cluster	0.300	1,265	clusters remove 21% of switches, no pos
SORT (same stream)	0.493	263	ignores appearance
ByteTrack (same stream)	0.496	235	ignores appearance
DeepSORT (same stream)	0.458	309	trusts appearance—degraded

E. Detector stress, self-calibration, and the audit

Under a real YOLOv8-pose stream (recall ~ 30 –35%, median person ≈ 34 px tall), every tracker collapses to the detection floor; the comparison becomes a detection-recall test. The velocity gate cuts motion_reid’s MOT17-04 IDSW 33 $\rightarrow$ 15, raises IDF1 by 3 pp, and closes the gap to SORT to 0.7 pp (0.177 vs. 0.184; HOTA 0.599 competitive with the appearance trackers on the same stream); on MOT17-02 a residual switch cost remains (48 vs. 13–15). A recall sweep (80/60/40% subsampling) shows the ranking does not flip as recall falls—the system is association-limited, not recall-limited. The two transfer constants are derivable from the detection stream alone (self-calibrated 9.1/13.7 px/frame vs. GT-derived 8.0/12.0, within 14%), and a channel-calibration audit (remove the channel; IDF1 must not rise) flags both appearance channels we tested as net-harmful. Full per-sequence tables, the detector-recall audit, and the self-calibration comparison are in the supplementary material.

IV. CONCLUSION

An identity architecture in which motion is the primary signal and the decision layer—not the channel models—is the portable contribution. Synthetic hard segments: statistically zero identity switches through every interruption that breaks appearance. MOT17: the pose-free group-level mechanism cuts identity switches by 21% (1,265 $\rightarrow$ 995), a velocity gate closes most of the detector-stress gap, self-calibration removes the ground-truth dependence of the transfer constants, and a generalizable audit shows uncalibrated appearance channels harm every tracker that trusts them. The architecture, the honest measurement protocol, and the two upgrade paths (calibrated appearance, real-skeleton gait) are stated rather than assumed.

COMPLIANCE STATEMENTS

Conflict of Interest. The authors declare no conflict of interest.

Compliance with Ethical Standards. This work uses synthetic simulated data and the publicly available MOT17 benchmark; no human subjects, personal data, or ethical approval was required. All measurements are reproducible from the released code and result files.

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