Recovering Origin–Destination Flows from Bus CCTV: Early Results from Nairobi and Kigali

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Motivation: Why OD from CCTV?

Public transport in sub-Saharan Africa (SSA) is dominated by buses and matatus that routinely operate over capacity.

Agencies still rely on manual OD surveys that are:

- infrequent and expensive
- hard to scale
- blind to illegal roadside stops and detailed in-vehicle flows.

Existing automated approaches (AFC, APCs, RFID, mobile phone data) are:

- hardware-heavy, high-maintenance
- often not deployed at scale in SSA
- usually provide aggregate counts, not passenger-level OD.

Key idea: Use CCTV that already exists for security + telematics to recover passenger-level OD flows with minimal extra hardware.

Contribution

1. Baseline 4-stage CCTV + telematics pipeline for OD inference tailored to SSA buses.
2. Deployment on real buses in Nairobi and Kigali using only existing CCTV + telematics—no extra sensors.
3. Quantitative evaluation on annotated short clips:
   - High accuracy under low-density, well-lit conditions
   - Sharp degradation under overcrowding, modality shifts, posture changes, and non-standard door use.
4. Simple, domain-informed fixes (door-state gating + flexible stop definition) that substantially boost exit-door accuracy without changing the detector or Re-ID backbone.

Takeaway: We can already recover useful OD matrices from messy SSA CCTV, but door context and telematics matter more than just better CNNs.

UrbanAI Context

Setting: Buses in Nairobi (Kenya) and Kigali (Rwanda) with onboard CCTV and telematics.

Typical challenges:

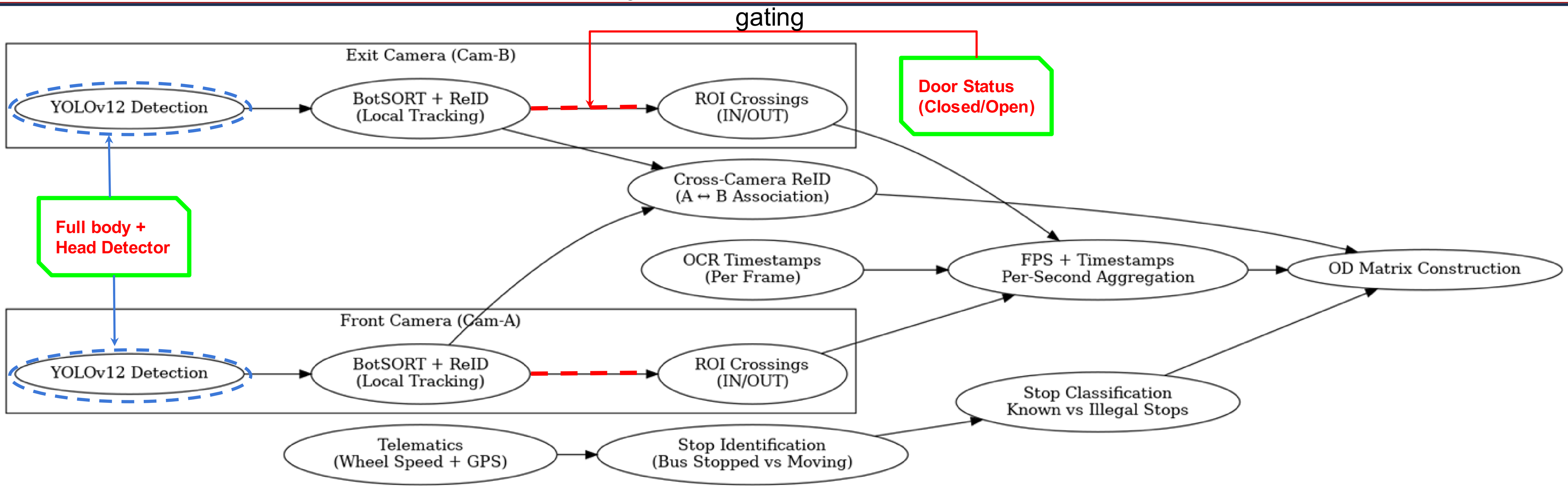
- Overcrowded doorways
- Low-resolution, sometimes monochrome CCTV
- Non-standard door usage
- Illegal stops in traffic, away from official bus stops.

Goal: Enable data-driven route design, equity analysis, and e-bus planning using vision + onboard sensors.

Data & Evaluation

- 11 CCTV segments, 3–8 minutes each.
- Conditions evaluated include low, medium and peak crowding, color vs monochrome segments and partial occlusions.
- Ground truth data contains per-door entry/exit counts and derived OD matrices per clip.

System Overview



Two–stream pipeline with new and enhanced modules highlighted. **Baseline (black):** Same logic for both cameras but works in low-crowd conditions. **Reality:** Exit door is a choke point → heavy occlusion, queues, posture changes.

Baseline Pipeline

- For each camera, detect and track passengers with BotSORT + ReID to get per-camera tracklets.
- Link tracklets from front camera (Cam-A) and exit door camera (Cam-B).
- OCR to extract on frame timestamp & aggregate ROI-based IN/OUT events into per-second counts.
- Use telematics data (GPS, wheel speed) to detect and classify stops.
- **New:** Use **head detection** for IN/OUT events during **overcrowding** and **activate** counter **ONLY** when door is **open**.
- For each passenger trajectory, identify **boarding stop** and **alighting stop** → increment cell in OD matrix.

Results

Entrance Video	Ground Truth		Baseline		Door State		Hybrid Det		All Together	
	IN	OUT	IN	OUT	IN	OUT	IN	OUT	IN	OUT
9:03 am	8	0	7	0	7	0	7	0	7	0
12:28 pm	40	1	39	0	39	0	39	0	39	0
7:45 pm	0	3	0	2	0	2	0	2	0	2
8:42 pm	1	0	1	0	1	0	1	0	1	0
9:11 pm	45	3	42	2	42	2	42	2	42	2

Exit Video	Ground Truth		Baseline		Door State		Hybrid Det		All Together	
	IN	OUT	IN	OUT	IN	OUT	IN	OUT	IN	OUT
9:03 am	0	0	0	1	0	0	0	1	0	0
9:34 am	3	1	3	2	3	1	3	2	3	1
12:28 pm	0	0	1	1	0	0	1	1	0	0
7:45 pm	0	0	0	0	0	0	0	0	0	0
8:42 pm	0	4	0	4	0	3	0	4	0	1
9:11 pm	0	0	0	0	0	0	0	0	0	0

- Hybrid detector does not improve exit accuracy on current segments vs baseline.
- **Takeaway**: Simple domain cues (door state, near-zero speed with open doors) fix more than just adding another detector.

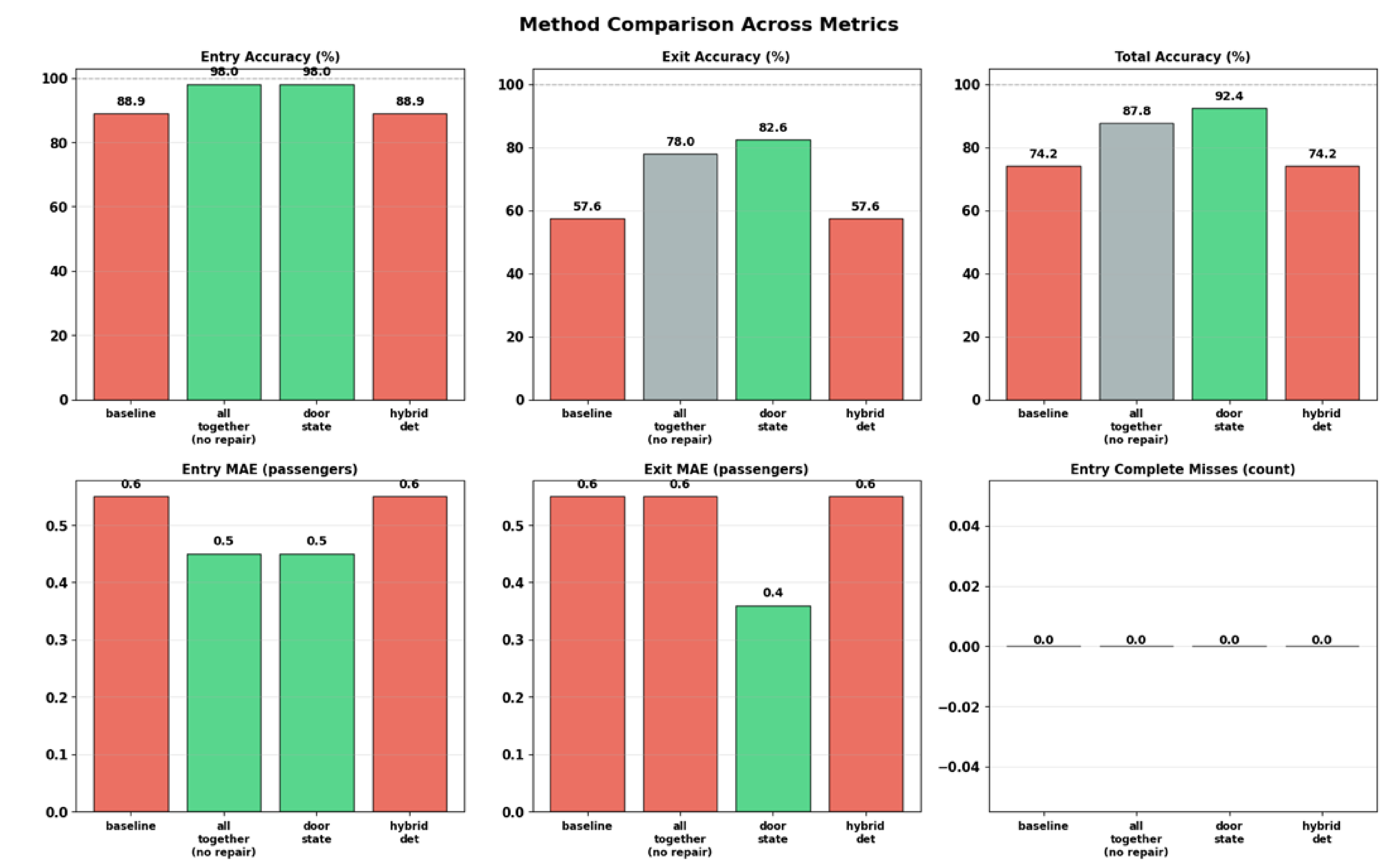


Table 1: Baseline pipeline accuracy under different operating conditions.

Condition	Detection	Tracking	OD Matrix Accuracy
Ideal (low density, good lighting)	40/42 correct, +4 FP	Stable IDs	Matches manual tallies
Overcrowding (peak hour)	Missed detections	Frequent ID switches	∼40% undercount
Poor lighting / shadows	Degraded confidence	Unstable IDs	Diverges at exits
Posture changes	Robust detections	Fragmented tracklets	Incomplete trips
Color ↔ B/W switching	Robust	Inconsistent features	∼17% degradation
Non-standard door use	Robust	Ambiguous direction	Noisy OD matrix

Deployment-Specific Challenges

- During overcrowding & occlusion at doors, only heads visible; tracklets fragment.
- Due to posture changes (standing, sitting, leaning) appearance embeddings drift; Re-ID continuity breaks.
- Modality shifts (color ↔ monochrome / IR) causes a drop in recall; embeddings unstable.
- Visual similarity (uniforms, similar clothing) cause identity switches; ambiguous matches.
- Boarding + alighting both doors cause a mismatch between direction of motion and door semantics.

Key Takeaways

- CCTV-only OD is feasible in low-resource settings when fused with telematics.
- Behavioral and operational context (door state, stop logic) is as important as model choice.
- Simple rules (door gating, near-zero speed with open doors) deliver big gains in exit-door accuracy.
- Failure under extreme crowding and modality shifts highlight the need for robust, deployment-aware Re-ID embeddings and trajectory-aware identity repair and motion-informed gating.

Next Steps

- Build stronger cross-camera, motion-aware gating + cost-optimal assignment for crowded doors.
- Controlled robustness studies by varying crowding and posture to quantify ID stability.
- Scale to full-day deployments and analyze equity impacts.
- Streamline the counter to be queue aware so that people waiting outside are not counted until they truly cross into or out of the vehicle.

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