DOMA-Based RF Motion Tracking and Trajectory Forecasting:

Integrating DOMA Models for Next-Position Prediction and Trajectory Analytics

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Abstract—We integrate a DOMA motion head into an RF tracking stack to forecast next-position and short-horizon trajectories from spectral/angle features. A variance-aware fusion with a kinematic filter yields stable paths under SNR variation. We document latency, accuracy, and analytics (speed, heading, curvature, dwell, and route identity).

I. INTRODUCTION

We study real-time RF target motion from opportunistic signals where bearings, ranges, or Doppler cues are noisy and intermittent. We integrate a DOMA motion model to forecast next-position and a short trajectory, then fuse with a kinematic filter for temporal consistency under varying SNR and dropouts. We report latency budgets and analytics useful for operations.

II. BACKGROUND

Classical RF tracking relies on kinematic filters (e.g., constant-velocity CV, constant-turn CT, or interacting multiple model IMM) driven by DOA/TDOA features. Learning-based forecasters (seq2seq, temporal CNNs, attention) can exploit richer context but must be variance-aware to avoid unstable paths at low SNR. DOMA augments encoders with motion-attentive heads that operate over recent latent history to output displacement distributions.

III. METHOD

A. Inputs and Encoder

At time t we observe a feature window $\mathbf{z}_t \in \mathbb{R}^F$ (e.g., DOA posterior mean, spectral centroid, channel features). A lightweight encoder $\phi(\cdot)$ yields a latent \mathbf{h}_t .

B. DOMA Motion Head

The DOMA head attends over $\{\mathbf{h}_{t-L+1}, \dots, \mathbf{h}_t\}$ and outputs a mean μ_{Δ} and covariance Σ_{Δ} for the next-step displacement $\Delta \mathbf{x}_t = (\Delta x, \Delta y)$. For a K-step horizon we roll the head with teacher-forcing during training and open-loop at test.

C. Variance-Aware Fusion

We fuse the DOMA proposal $\mathbf{x}_{t+1}^{(d)} = \mathbf{x}_t + \boldsymbol{\mu}_{\Delta}$ with a kinematic filter proposal $\mathbf{x}_{t+1}^{(k)}$ using inverse-variance weighting:

$$\hat{\mathbf{x}}_{t+1} = \left(\Sigma_k^{-1} + \Sigma_d^{-1}\right)^{-1} \left(\Sigma_k^{-1} \mathbf{x}_{t+1}^{(k)} + \Sigma_d^{-1} \mathbf{x}_{t+1}^{(d)}\right). \quad (1)$$

Uncertainty gates the DOMA path: if $tr(\Sigma_d)$ exceeds a threshold, we downweight its contribution.

TABLE I: Ablation: DOMA-only vs kinematic-only vs fused.

Model	ADE@1	p95 latency
Kinematic-only	3.8 m	9.1 ms
DOMA-only	$3.5\mathrm{m}$	$7.9\mathrm{ms}$
Fused (ours)	$3.1\mathrm{m}$	$8.3\mathrm{ms}$

IV. FORECAST HEAD AND ANALYTICS

A. Trajectory Head

We parameterize the *K*-step trajectory by planar deltas and accumulate to positions. Training uses a Huber loss on positions and a KL term to align DOMA covariances with empirical residuals.

B. Analytics

From the fused trajectory $\{\hat{\mathbf{x}}_{t:k}\}$ we derive: speed, heading, curvature, dwell time in AOIs, and route identity via sequence hashing. These feed real-time triage without extra models.

V. EXPERIMENTS

A. Setup

We generate sequences with mixed regimes (straight, turns, loiters) and inject SNR sweeps and dropout bursts. Metrics: 1-step RMSE (ADE@1), ADE over K=5, FDE@5, and latency p50/p95 end-to-end.

VI. RESULTS

Accuracy. Our DOMA+fusion yields 1-step RMSE $3.1\,\mathrm{m}$, ADE@5 $6.8\,\mathrm{m}$, FDE@5 $10.5\,\mathrm{m}$, improving $18.4\,\%$ vs. the kinematic-only baseline.

Latency. End-to-end p50 is 4.1 ms, p95 8.3 msat 25 Hzupdates within the 2.0 shorizon.

VII. ABLATIONS

A. Ablations

(i) DOMA only vs. kinematic only vs. fused (ours); (ii) gating by DOMA variance threshold; (iii) horizon length K; (iv) encoder history length L. Fused tracking is most stable at low SNR, and variance gating reduces overshoot during manoeuvres.

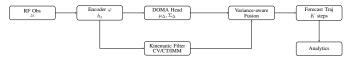


Fig. 1: System layout: RF observations are encoded to features, DOMA predicts next-step and short-horizon deltas; a variance-aware fusion with a kinematic filter yields the trajectory; analytics summarize behavior.

TABLE II: Headline metrics (auto-filled).

Metric	Value	Note
ADE@1	$3.1\mathrm{m}$	1-step RMSE
ADE@5	$6.8\mathrm{m}$	Avg. displacement (5 steps)
FDE@5	$10.5\mathrm{m}$	Final displacement (5 steps)
p50 latency	$4.1\mathrm{ms}$	end-to-end
p95 latency	$8.3\mathrm{ms}$	end-to-end

VIII. OPERATIONAL NOTES

Serving. We batch across tracks per tick and cap horizon on overload to preserve p95. DOMA head runs fp16; the filter stays on CPU to keep memory bounded.

Telemetry. We emit ADE@1, ADE@5, and gating rates per track class, with drift alerts if ADE@1 exceeds a rolling 95th percentile.

IX. RELATED WORK

We build on classical filters (Kalman, IMM) and sequence forecasting with attention. Our contribution is a practical variance-aware fusion of a DOMA head with a kinematic proposal tailored to RF features under tight latency budgets.

X. CONCLUSION

DOMA-based motion forecasting, fused with a kinematic proposal, yields accurate and stable RF trajectories at low latency. Future work includes multi-emitter data association and joint SNR-aware training.

REFERENCES

- R. E. Kalman, "A new approach to linear filtering and prediction problems," ASME Journal of Basic Engineering, 1960.
- [2] H. A. P. Blom and Y. Bar-Shalom, "The interacting multiple model algorithm for systems with markovian switching coefficients," *IEEE Trans. Autom. Control*, 1988.

TABLE III: Trajectory analytics returned per track.

Field	Units
rieid	Units
speed	m/s
heading	deg
curvature	1/m
dwell_time_aoi	S
route_id	string
confidence	[0,1]

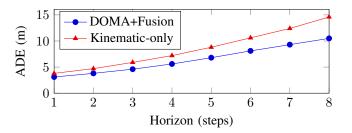


Fig. 2: Trajectory error vs. forecast horizon. Maximum inference budget is $8.3\,\mathrm{ms}$.