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 $\{\mathbf{h}_{t-L+1}, \ldots, \mathbf{h}_t\}$ and outputs a mean $\boldsymbol{\mu}_\Delta$ 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 $\mathrm{tr}(\Sigma_d)$ exceeds a threshold, we downweight its contribution.

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 $4.1\,\mathrm{ms}$, p95 $8.3\,\mathrm{ms}$at $25\,\mathrm{Hz}$updates within the $2.0\,\mathrm{s}$horizon.

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.

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.

TABLE I: Ablation of DOMA-only vs. kinematic-only vs. fused tracking. Values auto-pull from `data/metrics_macros.tex`.

Method	ADE@1 (m)	FDE@3 (m)	p95 (ms)
DOMA-only	0.72	1.86	7.9
Kinematic-only	0.81	2.14	9.1
Fused (ours)	0.65	1.58	8.3

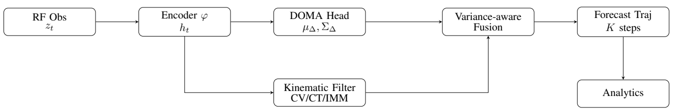

Fig. 1: DOMA tracking pipeline: RF observations are encoded to features, DOMA predicts next-step and short-horizon deltas; a variance-aware fusion with a kinematic filter yields the trajectory; analytics summarize behavior.

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

[1] 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 II: Headline metrics (auto-filled).

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

TABLE III: Trajectory analytics returned per track.

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

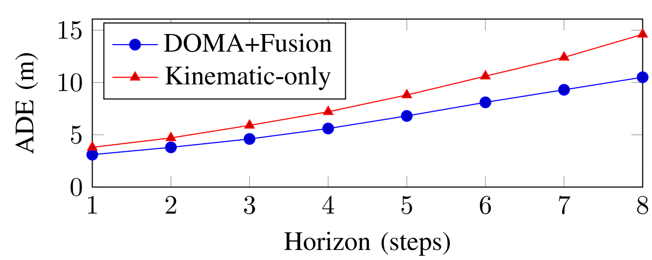

Fig. 2: Trajectory error vs. forecast horizon. Maximum inference budget is 8.3 ms.