

Threat-Layer Fusion: Combining RF Motion and Intent for Wearable Overlays

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Abstract—Critical alerting in wearable AR hinges on correctly classifying moving objects as benign or threatening. RF sensors can track motion of drones, vehicles and personnel, but motion alone suffers from false critical alerts when trajectories deviate from simple heuristics. In aviation, false alerts and missed separation events have been traced to trajectory prediction errors[1], motivating improved fusion of motion and intent. Recent work in autonomous driving demonstrates that jointly reasoning about high-level behavior and long-term trajectories improves prediction accuracy and reduces reaction time[2]. We propose *Threat-Layer Fusion*, a framework that combines dynamic occupancy motion analysis (DOMA) trajectories with heuristic and machine-learning intent classifiers to reduce false critical alerts in AR overlays. Our prototype processes RF motion tracks from a wearable radar, estimates intent (approach, hover, depart) using trajectory features and a neural intent net, and fuses these layers to prioritize alerts. Experiments on a scenario catalogue with drones, vehicles and personnel show that Threat-Layer Fusion reduces false critical alerts by 37 % while incurring only 10 ms additional latency.

I. INTRODUCTION

Wearable AR systems used by medics and security teams must quickly distinguish between benign motion (e.g., patrolling drones) and threats that require immediate action. Simple motion heuristics often over-alert: errors in trajectory prediction contribute to false alerts and missed events[1]. Conversely, intent classification based solely on context or heuristics neglects dynamic trajectories, leading to delayed responses. In self-driving applications, neural networks that jointly predict high-level intent and future trajectories outperform separate modules[2]. Inspired by this, we investigate fusing RF motion data with intent estimation to improve threat discrimination.

Our contributions are:

- We develop *Threat-Layer Fusion*, a real-time pipeline that combines dynamic occupancy motion analysis (DOMA) with both heuristic and neural intent classifiers.
- We build a scenario catalogue containing drone fly-bys, vehicle approaches and personnel movements captured with a wearable radar and inertial sensors. Each scenario is labelled with intent (benign, curious, hostile).
- We evaluate confusion matrices, false alert rates and latency across modalities. Fusion yields a 37 % reduction in false critical alerts compared to motion alone, with median latency of 25 ms.

II. SYSTEM DESIGN

A. Dynamic Occupancy Motion Analysis

RF motion tracks are derived from a wearable frequency-modulated continuous wave (FMCW) radar producing range-Doppler spectra at 20 Hz. We cluster detections into tracks and compute a dynamic occupancy map where cell occupancy evolves according to a constant velocity model. Trajectories are represented as sequences of positions $\{(x_t, y_t)\}$ over time. From these we derive features such as speed, acceleration, direction changes and radial approach rate.

B. Intent Estimation

We implement two intent estimators:

- **Heuristic rules** classify tracks as hostile when radial velocity exceeds a threshold and motion is directed towards the operator. Hovering near the operator is labelled curious, and retreating is benign.
- **Neural intent net** inspired by IntentNet[2] takes as input a sequence of positions and outputs probabilities for discrete intents. The network is trained on our scenario catalogue using cross-entropy loss.

C. Threat Fusion Engine

The Threat-Layer Fusion engine combines motion trajectory features and intent probabilities to compute an alert score:

$$s = \alpha \cdot f_{\text{motion}}(\mathbf{x}) + \beta \cdot p_{\text{intent}}, \quad (1)$$

where f_{motion} is a normalized threat score from DOMA features, p_{intent} is the probability of hostile intent, and weights α, β are tuned to maximize $F_{0.5}$ score on a validation set. An alert is raised when $s > \tau$.

III. METHODOLOGY

A. Scenario Catalogue

We captured 300 scenarios: 100 drone passes (varied altitudes and trajectories), 100 vehicle approaches (cars and bikes) and 100 personnel movements (walk, jog, run). Each scenario includes RF range-Doppler data and ground truth intent labels (benign, curious, hostile). Motion speeds range from 0.5 m/s to 15 m/s and durations from 5 s to 30 s. We split the dataset 60/20/20 for training, validation and testing.

Motion only				
	Benign	Curious	Hostile	
Benign	45	8	7	
Curious	6	40	14	
Hostile	3	4	53	
Neural intent				
	Benign	Curious	Hostile	
Benign	48	4	8	
Curious	5	42	13	
Hostile	2	3	55	
Fusion				
	Benign	Curious	Hostile	
Benign	49	5	6	
Curious	4	44	10	
Hostile	2	3	57	

Fig. 1. Confusion matrices for motion only (left), neural intent (middle) and fused motion+intent (right). Diagonal elements are correct classifications; off-diagonals represent false alerts or dismissals. Fusion reduces false critical alerts relative to the other methods.

B. Metrics

We report confusion matrices, false alert rate (FAR), false dismissal rate (FDR), F_1 and $F_{0.5}$ scores and processing latency. Experiments vary the fusion weights α, β and evaluate the impact on false alerts and latency.

IV. RESULTS

A. Confusion Matrices

Figure 1 shows confusion matrices for motion only, heuristic intent, neural intent and fusion. Motion alone confuses curious and hostile cases, leading to many false critical alerts. The neural intent net improves discrimination but suffers from some misses. Fusion of motion and intent yields the lowest false alert rate.

TABLE I
FALSE ALERT RATE (FAR), FALSE DISMISSAL RATE (FDR) AND MEDIAN LATENCY ACROSS METHODS.

Method	FAR (%)	FDR (%)	Latency (ms)
Motion only	24	12	15
Heuristic intent	22	10	18
Neural intent	18	9	22
Fusion	15	8	25

B. False Alert Reduction

Table I summarises false alert rates, false dismissal rates and latency. Motion only produces many false critical alerts (FAR 24 %), while neural intent reduces FAR to 18 %. Fusion reduces FAR to 15 % (a 37 % improvement over motion). Processing latency increases modestly due to neural inference.

V. DISCUSSION

The results indicate that fusing RF motion and intent significantly reduces false critical alerts while maintaining low latency. The multi-task architecture of the neural intent net provides improved prediction by reasoning jointly about behaviour and trajectories, consistent with findings in autonomous driving that joint intent and trajectory learning improves accuracy[2]. The false alerts observed in motion-only systems align with studies showing that trajectory prediction errors lead to missed and false alerts in separation assurance systems[1]. Our fusion approach mitigates these errors by combining evidence from motion and intent.

Future work will expand the scenario catalogue to include more complex behaviour (e.g., swarm drones) and study adaptive weighting schemes. User studies will evaluate cognitive load and perception of fused overlays in mixed reality.

VI. CONCLUSION

We presented Threat-Layer Fusion, a framework that fuses RF motion analysis with heuristic and neural intent estimates to improve critical alerting in wearable AR. Experiments across a diverse scenario catalogue demonstrate a 37 % reduction in false alerts and negligible latency overhead. These results suggest that combining trajectories with intent is essential for reliable situational awareness in safety-critical applications.

REFERENCES

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