Millimeter-Wave Beam Prediction with Inverse Beamforming ML Model

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Signal Processing for Communications and Networking
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1. Introduction

- Effective **beam management is crucial** for mmWave wireless systems.
- **Tracking techniques** operate solely on received signals help **avoid additional radio resource consumption**.
- Most **existing ML-based tracking approaches** focus on estimating the **current AoA** or require high-complexity models.
- **Our ML approach** predicts the **next-step AoA** by analyzing prior AoA values and received signals from the beamformer output, using a low-complexity model.
- The **EKF serves as a benchmark** due to its effectiveness in nonlinear estimation problems.

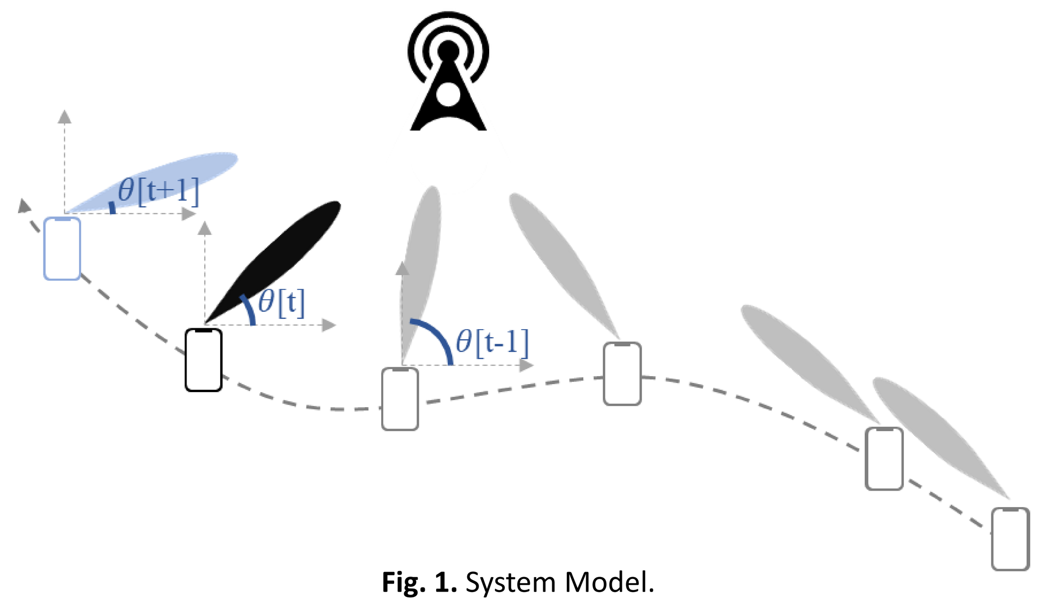

Fig. 1. System Model.

2. System Model and Data Generation

We simulated a mmWave scenario with a BS, communicating with UEs moving with varying speeds and orientations. Equation (1) defines the steering vector, equation (2) defines the channel observation [1], [2], and the simulation parameters are summarized in the table below.

$$\boldsymbol{a}(\theta) = \left[1, e^{jkd\cos(\theta)}, \dots, e^{jkd(N-1)\cos(\theta)}\right]^T \quad (1)$$

$$y[t] = \frac{\alpha[t]}{N}\, \boldsymbol{w}^H\big(\hat{\theta}[t]\big)\, \boldsymbol{a}(\theta[t]) + n[t] \quad (2)$$

Table 1. Simulation Parameters.

Parameter	Value
Cell Radius	60 meters (BS at the center)
Carrier Frequency	28 GHz
BS Antenna	Omnidirectional
UE Antenna	ULA / N ∈{4, 8, 12, …, 64}
Prediction period	0.1 seconds
α Model	First-Order Gauss-Markov
Users speed	speed ∈ [1, 33] m/s
Users orientation	Varying orientation

$k = 2\pi/\lambda$
λ: the signal wavelength
d: the distance between adjacent antenna elements
θ: the true AoA
N: the antenna number at the UE
$\alpha[t]$: the complex gain of the dominant path
$\boldsymbol{a}(\theta[t])$: the steering vector
$\boldsymbol{w}(\hat{\theta}[t])$: the weighting vector
$(.)^H$: the Hermitian operator (complex conjugate transpose)
$n[t]$: the additive noise
$\theta[t]$ and $\hat{\theta}[t]$: the true and predicted AoA respectively

- A single **dominant multipath component** is tracked.
- We assume an **initial BS-UE connection is established**, the challenge is maintaining it.

3. ML Solution

Our ML-based solution leverages an LSTM network for their ability to capture long-term dependencies in time-series data.

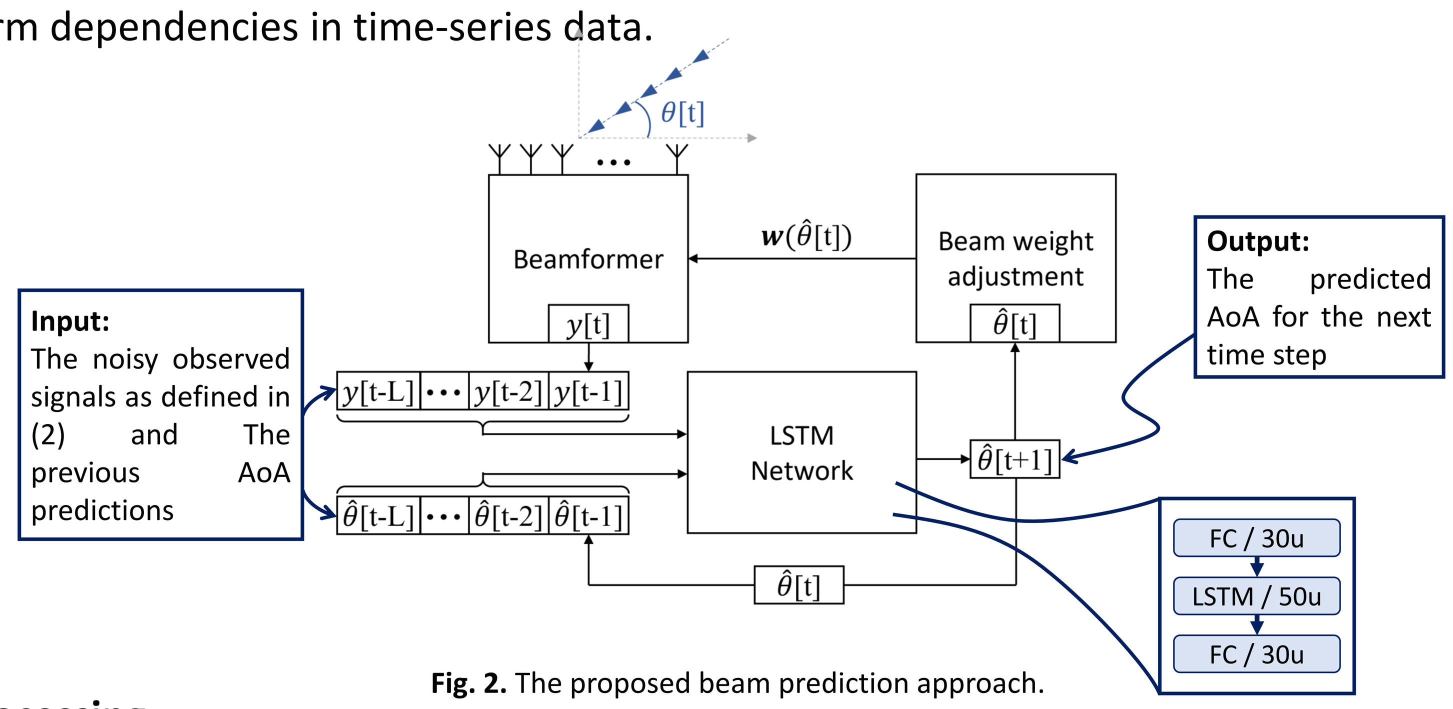

Fig. 2. The proposed beam prediction approach.

Processing:

- The sequence length L determines the number of prior states considered
- We assume that the model performs an inverse beamforming process on the observed signals to extract the AoA. By analyzing prior AoA values, it captures the underlying temporal dependencies and variation patterns in the data.
- An initial sequence of historical AoA values and channel observations (of length L) is assumed to be known.

4. Evaluation Metrics

We evaluate the performance using two key metrics:

- **The outage probability** quantifies the likelihood of a connection loss and is defined as:

$$P = \frac{1}{M}\sum_{m=1}^{M} I\left[\left|\theta_m - \hat{\theta}_m\right| > \Delta\theta_{Th}\right] \quad (3)$$

θ_m and $\hat{\theta}_m$ represent the true and predicted AoA at the the m-th instance
M: represents the total number of predictions
$\Delta\theta_{Th} = \frac{4\pi}{3N}$: threshold angle determined as a function of the UE antennas.

- **The Root Mean Squared Error** determines the accuracy of $\hat{\theta}$ and is calculated as:

$$RMSE = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(\theta_k - \hat{\theta}_k\right)^2} \quad (4)$$

θ_k and $\hat{\theta}_k$ are the true and predicted AoA at the k-th instance (for non-outage cases)
K: is the total number of such non-outage instances.

5. Results

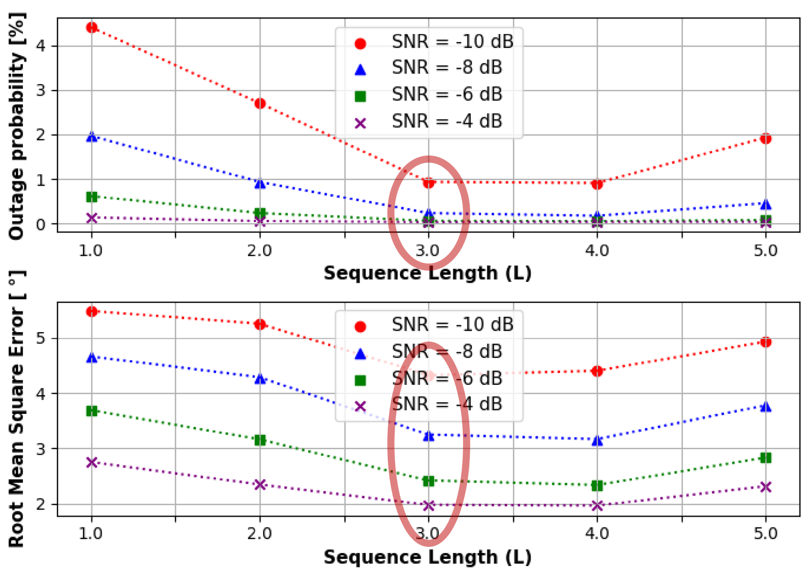

Fig. 3. Outage probability and RMSE as a function of Sequence Length for ML solution.

Selecting an **optimal sequence length** provides enough historical data for accurate predictions without overwhelming the model. Based on these observations, we select a sequence length of L=3 for the remainder of the results.

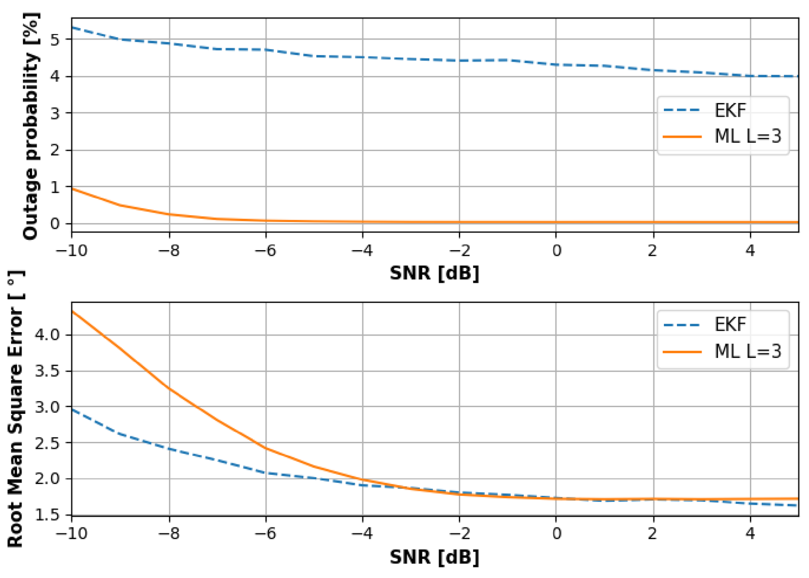

Fig. 4. ML vs. EKF: Outage probability and RMSE as a function of SNR.

Across all SNR values, the ML solution achieves **lower outage probability than the EKF**. At lower SNRs, the ML model shows a higher RMSE because it prioritizes maintaining a reliable connection over precise angle prediction.

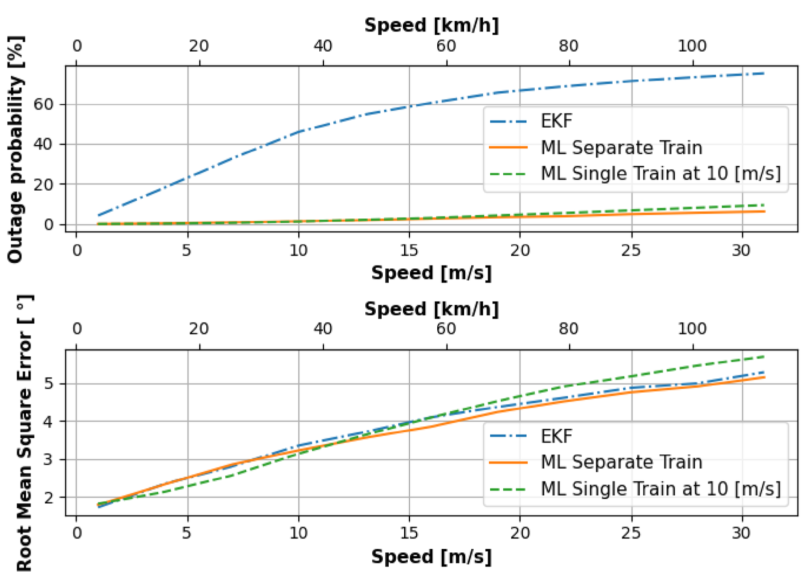

Fig. 5. Outage probability and RMSE as a function of speed.

Both ML approaches outperform the EKF. While separate training yields slightly better performance than single training, the small difference underscores the model's **robust generalization across varying user speeds**.

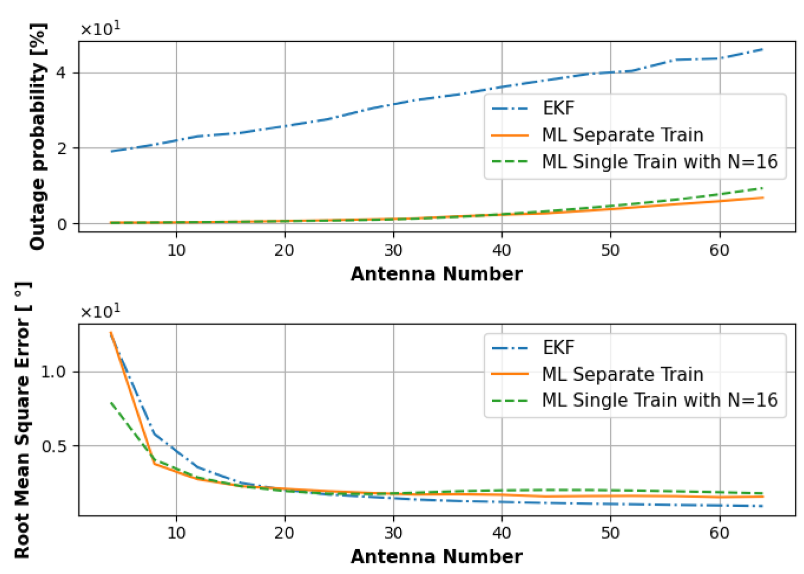

Fig. 6. Outage probability and RMSE as a function of the number of antennas.

Again, both ML methods outperform the EKF. Moreover, separate training slightly outperforms single training, highlighting the model's **adaptability and ability to generalize across different setups**.

Conclusion

- The proposed **ML method significantly reduces outage probability**, thereby enhancing mmWave link.
- By enhancing beam steering reliability, **reduces the need for frequent beam searches** (up to 8 times).
- Our approach shows **robust adaptability**, performing strongly even when trained on a single configuration (maximum difference of only 0.2%).

References

[1]. L. Chen, S. Zhou, and W. Wang, MmWave Beam Tracking With Spatial Information Based on Extended Kalman Filter, IEEE Wirel. Commun. Lett., Vol. 12, Issue 4, 2023, pp. 615-619.
[2]. S. H. Lim, S. Kim, B. Shim, and J. W. Choi, Deep Learning-Based Beam Tracking for Millimeter-Wave Communications Under Mobility, IEEE Trans. Commun., Vol. 69, Issue 11, 2021, pp. 7458-7469.