Robust Vehicle Localization Based on Adaptive DOA Estimation and UKF under Varying Interference Conditions

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***Abstract*—Accurate localization in GPS-denied environments is vital for ITS and vehicular networks. While Root-MUSIC offers high accuracy in clean LoS conditions, FBSS enhances robustness under multipath and interference. To overcome the limitations of fixed estimators, this paper proposes an adaptive DOA-based localization framework that selects Root-MUSIC+UKF in low-interference regimes and FBSS-Root-MUSIC+UKF when interference is strong. Simulations show that the proposed method consistently reduces positioning error across varying SNR and interference levels, providing reliable GPS-free vehicle localization in non-stationary wireless environments.**

***Index Terms*—DoA estimation, Root-MUSIC, FBSS, UKF, vehicle localization, adaptive framework.**

I. Introduction

Accurate localization is fundamental to ITS, autonomous driving, and vehicular communications, yet GPS suffers severe degradation in urban canyons, tunnels, and NLoS scenarios. DOA-based localization provides high-resolution positioning without relying on GPS or additional infrastructure. In [1], Paaso et al. proposed a forward-backward spatial smoothing (FBSS) enhanced MUSIC algorithm to improve angular resolutions. Similarly, Liu, et al. [2] developed an enhanced root-MUSIC method based on multi-resolution composite arrays (MRCAs), .

MUSIC and its variants remain central to DOA estimation research. Prior works have shown that FBSS improves robustness against coherent interference, while Root-MUSIC offers high accuracy and computational efficiency under interference-free conditions. These findings highlight a tradeoff between robustness and accuracy. Motivated by this, we propose an adaptive framework that switches between Root-MUSIC and FBSS-Root-MUSIC based on interference levels and integrates DOA estimation with UKF for improved tracking.

The main contributions are as follows:

- **DOA–UKF integration:** Combining DOA estimation with UKF for accurate, nonlinear bearing-only vehicle tracking.
- **Adaptive estimator selection:** Dynamically choosing Root-MUSIC or FBSS-Root-MUSIC depending on interference conditions.
- **Comprehensive simulations:** Evaluating multiple Kalman filters and MUSIC-type algorithms, demonstrating the accuracy and robustness of the proposed approach.

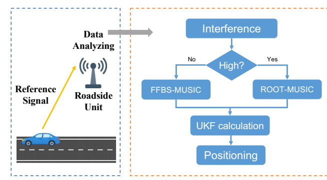

Fig. 1: The system framework.

II. System model

A. Description

We consider bearing-only vehicle localization using a roadside unit (RSU) equipped with a uniform linear array (ULA) as shown in Fig .1. The array front-end produces a DOA estimate that is fed to a state estimator (UKF). All equations are presented in order.

The 2-D state is

$$\mathbf{x}_k \triangleq \begin{bmatrix} x_k & y_k & v_{x,k} & v_{y,k} & a_{x,k} & a_{y,k} \end{bmatrix}^\top \in \mathbb{R}^6. \tag{1}$$

where $\ell = 1, 2, \ldots, L$ is the snapshot index within time step k.

MUSIC::

$$P_{\mathrm{MU}}(\theta) = \frac{1}{\mathbf{a}(\theta)^H \mathbf{E}_n \mathbf{E}_n^H \mathbf{a}(\theta)}, \qquad \widehat{\theta}_k = \arg\max_{\theta \in \Theta} P_{\mathrm{MU}}(\theta). \tag{2}$$

(When FBSS is used, replace $\mathbf{a}(\theta)$ by the m-element subarray steering vector.)

Root-MUSIC (ULA):: Let $\mathbf{b}_r(z) = [1, z, \ldots, z^{r-1}]^\top$ with $r = M$ (no smoothing) or $r = m$ (FBSS).

Given an interference threshold Γ, the DOA front-end is chosen as

$$\widehat{\theta}_k = \begin{cases} \widehat{\theta}_k^{\text{Root-MUSIC}}(\widehat{\mathbf{R}}_{xx,k}), & \text{if } \mathrm{INR}_k \le \Gamma, \\ \widehat{\theta}_k^{\text{FBSS-Root}}(\widehat{\mathbf{R}}_{\mathrm{FBA},k}), & \text{if } \mathrm{INR}_k > \Gamma. \end{cases} \tag{3}$$

B. Tracking with Unscented Kalman Filter (UKF)

To estimate the vehicle trajectory from the noisy DoA measurements, we employ the Unscented Kalman Filter (UKF). The UKF is well-suited for nonlinear systems, as it propagates a set of deterministically chosen *sigma points* through the

Algorithm 1: Adaptive DOA-based Vehicular Localization Framework

Input: Received snapshots $\mathbf{X}$, array parameters, interference threshold γ, previous vehicle state $\hat{\mathbf{x}}_{k-1}$.

Output: Estimated vehicle state $\hat{\mathbf{x}}_k$.

Step 1: Signal Preprocessing
  Compute covariance matrix $\mathbf{R}_{xx} = \frac{1}{L}\mathbf{X}\mathbf{X}^H$.
  Estimate SINR from $\mathbf{R}_{xx}$.
Step 2: Adaptive DOA Estimation
  if *SINR* $> \gamma$ *(low interference)* **then**
    Apply Root-MUSIC to estimate DOA $\hat{\theta}_k$;
else
    Apply FBSS + Root-MUSIC to estimate DOA $\hat{\theta}_k$;
Step 3: State Update with UKF
  Convert DOA measurement $\hat{\theta}_k$ into bearing observation z_k;
  Perform UKF prediction and update to obtain new vehicle state $\hat{\mathbf{x}}_k$;
Return: Vehicle state estimate $\hat{\mathbf{x}}_k$.

TABLE I: Simulation Parameters

Parameters	Values
Antenna spacing d	0.5λ
Snapshots (Seg. 1 / Seg. 2)	$32/20$
Interference angle	$-25°$ / $-30°$
Process noise covariance Q	$0.01\mathbf{I}_6$
Measurement noise variance R	$(1°)^2$ (in rad)
Sampling interval Δt	0.02 s

nonlinear functions instead of relying on Jacobian linearization as in the EKF.

1) State Transition Model: The system state vector is defined as

$$\mathbf{x}_k = \begin{bmatrix} x_k & y_k & v_{x,k} & v_{y,k} & a_{x,k} & a_{y,k} \end{bmatrix}^T, \tag{4}$$

where (x_k, y_k) is the position, $(v_{x,k}, v_{y,k})$ is the velocity, and $(a_{x,k}, a_{y,k})$ is the acceleration.

Finally, the Kalman gain and update equations are

$$\begin{cases} \mathbf{K}_k = \mathbf{P}_{xz} S_k^{-1}, \\ \mathbf{x}_{k|k} = \mathbf{x}_{k|k-1} + \mathbf{K}_k \big(z_k - \hat{z}_{k|k-1}\big), \\ \mathbf{P}_{k|k} = \mathbf{P}_{k|k-1} - \mathbf{K}_k S_k \mathbf{K}_k^T. \end{cases} \tag{5}$$

And we summrize the idea into the Algorithm 1 in the paper.

III. Numerical results

A. Simulation results

Fig. 2 and Fig. 3 shows the absolute NMSE for MUSIC and position error for different DOA–filtering schemes. In the first half of the experiment (low SNR, no interference), all approaches achieve similar error levels, with Root-MUSIC and FBSS-Root-MUSIC combined with UKF providing slightly

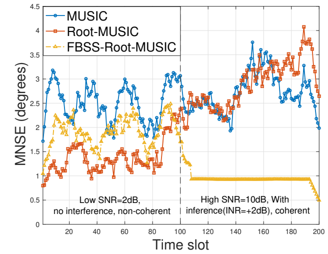

Fig. 2: MUSIC NMSE without (0-T/2) and with noise (T/2-T).

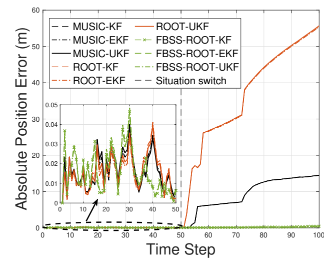

Fig. 3: The trajectory error under different scheme.

more stable performance. However, once strong interference is introduced (after the situation switch), Root-MUSIC-based filters quickly diverge, especially ROOT-UKF, leading to significant error accumulation. In contrast, FBSS-Root-MUSIC maintains consistently low error across all filters, with FBSS-Root-UKF achieving the best overall accuracy. This confirms that FBSS spatial smoothing effectively mitigates coherent interference, and its integration with UKF yields the most reliable tracking performance in realistic scenarios.

IV. Conclusion

Our study shows that Root-MUSIC performs best in low interference, while FBSS-Root-MUSIC is more robust under strong interference, and UKF consistently outperforms KF and EKF for nonlinear bearing tracking. Based on these findings, we developed an adaptive scheme that selects Root-MUSIC+UKF or FBSS-Root-MUSIC+UKF according to interference strength, achieving reliable localization in complex environments. Future work will extend the framework to multi-vehicle and RIS-assisted systems.

Acknowledgments

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