Data-Driven Indoor Localization and Mobility Tracking Using LSTM-Based Feature Learning

L.P.S.S. Dissanayake[1,3]*, M.B. Dissanayake[1], S.A.H.A. Suraweera[1], M.W.P. Maduranga[2]

[1]*Department of Electrical and Electronic Engineering, University of Peradeniya, Peradeniya, 20400, Sri Lanka*
[2]*Department of Electrical and Electronic Engineering, University of Sri Jayewardenepura, Gangodawila, Nugegoda, 10250, Sri Lanka*
[3]*Department of Network Technology, University of Vocational Technology, Ratmalana, 10390, Sri Lanka*
**suranga@uovt.ac.lk*

Indoor localization of mobile users remains a challenging problem due to the general unavailability of reliable GPS coverage in indoor environments. Radio signal-based positioning is further affected by multipath propagation, non-line-of-sight (NLOS) conditions, and measurement noise, which limit the accuracy of conventional model-based techniques such as Time of Arrival (TOA) and Direction of Arrival (DOA). This study investigates the effectiveness of Long Short-Term Memory (LSTM)-based localization and compares its performance with classical approaches, including TOA-only, DOA-only, TOA–DOA fusion, and Kalman filtering, under identical evaluation conditions. A dataset comprising 5,000 samples was generated in a 20 m × 20 m indoor environment using three anchor nodes, with user mobility modeled through random-walk trajectories at a movement speed of 2 m/s and signal measurements collected at 2 ms intervals. For each time step, raw RF signal features (correlation, amplitude, phase) and model-based features (estimated TOA, DOA, and distance) were extracted. The dataset was split into training and validation sets using a 70:30 ratio, and all classical baselines were optimized under the same conditions as the LSTM models to ensure a fair comparison. Performance was evaluated on a common held-out test set using Root Mean Square Error (RMSE), 90th-percentile error (P90), and Cumulative Distribution Function (CDF) analysis. Classical approaches yielded the highest errors, with RMSE values of 5.34 m (TOA-only) and 9.64 m (DOA-only), while TOA–DOA fusion and Kalman filtering provided only moderate improvements (7.33 m and 7.10 m RMSE, respectively). In contrast, LSTM-based models significantly outperformed all conventional methods, achieving RMSE values of 1.18 m using model-based features and 0.87 m using raw RF features, with corresponding P90 errors of 1.60 m and 1.34 m; CDF analysis further confirmed the superior reliability of the raw RF-based model. Inference times for TOA, DOA, and the best-performing LSTM model were also evaluated. Overall, the results demonstrate that raw RF signal characteristics contain richer localization information than derived model-based features, and that LSTM-based learning provides a promising solution for accurate real-time indoor positioning, though future work should address computational complexity, inference efficiency, and scalability for large-scale deployment.

Keywords: indoor positioning, mobile user tracking, data-driven learning, LSTM, TOA/DOA