# IoT-TD: IoT Dataset for Multiple Model BLE-based Indoor Localization/Tracking


1st Mohammad Salimibeni
*Concordia Institute for Inf. Systems Eng., Concordia University,*
Montreal, Canada
m_alimib@encs.concordia.ca

2nd Zohreh Hajiakhondi-Meybodi
*Electrical & Computer Engineering, Concordia University,*
Montreal, Canada
z_hajiak@encs.concordia.ca

3rd Parvin Malekzadeh
*Electrical & Computer Engineering, Concordia University,*
Montreal, Canada
p_malekz@encs.concordia.ca

4th Mohammadamin Atashi
*Electrical & Computer Engineering, Concordia University,*
Montreal, Canada
m_atashi@encs.concordia.ca

5th Konstantinos N. Plataniotis
*Electrical & Computer Engineering, University of Toronto,*
Toronto, Canada
kostas@ece.utoronto.ca

6th Arash Mohammadi
*Concordia Institute for Inf. Systems Eng., Concordia University,*
Montreal, Canada
arash.mohammadi@concordia.ca



***Abstract*—Bluetooth Low Energy (BLE) is one of the key enabling technologies of the emerging Internet of Things (IoT) concept. When it comes to BLE-based dynamic indoor tracking, however, due to drastic fluctuations of the Received Signal Strength Indicator (RSSI), highly acceptable accuracies are not yet achieved. Although very recent introduction of BLE v 5.1 promises prosperous future for BLE-based dynamic tracking, the following two key issues are in the path: (i) Despite of being in the age of big data with huge emphasis on reproducibility of research, there is no unified dataset with precise ground truth available for performing dynamic BLE-based tracking, and; (ii) The main focus of existing works are on utilization of stand-alone models. The paper addresses these gaps. At one hand, we introduce a reliable dataset, referred to as the IoT-TD, leveraging specific set of four optical cameras to provide ground truth with millimeter accuracies. The introduced IoT-TD dataset consists of RSSI values collected from five BLE sensors together with synchronized Inertial Measurement Unit (IMU) signals from the target's mobile device. On the other hand, the paper introduces a multiple-model dynamic estimation framework coupling RSSI-based particle filtering with IMU-based Pedestrian Dead Reckoning (PDR). Experimental results based on the IoT-TD dataset corroborate effectiveness of multiple modeling fusion frameworks for providing enhanced BLE-based tracking accuracies.**



***Index Terms*—Indoor Tracking, Internet of Things (IoT), Pedestrian Dead Reckoning, Bluetooth Low Energy (BLE).**


## I. Introduction

Development of advanced and innovative indoor localization-based services (LBSs) has recently become a research focal point given increased and ongoing enthusiasm from both industry and academia on the Internet of Things (IoT) concept [1]–[5], with wide range of potential and futuristic IoT applications [6]. One of the most critical challenges in this regard is the unmet need to compute accurate dynamic estimates of the distance between sensing devices and an intended object/user via fluctuating Received Signal Strength Indicator (RSSI) [7]. Despite this recent surge of interest and extensive algorithmic development efforts to meet the needs of LBSs for indoor environments, low accuracy in dynamic BLE-based distance tracking/estimation is a major problem preventing existence of reliable and robust indoor tracking solutions [8].

**Literature Review**: Generally speaking, there are different methods [9], [10] to localize a user within an indoor environment. A great number of recent approaches use additional hardware, e.g., single or array of antennas, or complementary board chips, to estimate Angle of Arrival (AoA) or Angle of Departure (AoD) parameters to localize a user [11]. Alternatively, Time of Flight (ToF) or Time Difference of Arrival (TDoA) are considered as other possible approaches to localize a user within an indoor environment [12], [13]. In such cases, however, the need for synchronization of the sensors increases the complexity of the system. On the other hand, RSSI-based tracking/localization methods using Bluetooth Low Energy (BLE) have gained wide-spread. The BLE offers several advantages over alternative technologies such as WiFi and Ultra Wide-Band (UWB) such as its optimized low power consumption [14]. Despite its popularity, there are, however, different drawbacks associated with BLE as compromises had to be made to reduce and minimize power consumption.

It is important to mention that BLE-based RSSI values are mainly suitable for proximity localization (e.g., to identify a device being immediate, near, or far from a BLE beacon) [15]. When it comes to BLE-based micro localization and dynamic tracking, due to multipath fading and drastic RSSI fluctuations, existing algorithms fail to provide satisfactory results. Very recent introduction of the BLE v5.1 protocol promises prosperous future for BLE-based dynamic tracking via utilization of In-phase and Quadrature signals (I/Q samples) for angular array-processing but this is yet to materialized. The accuracy


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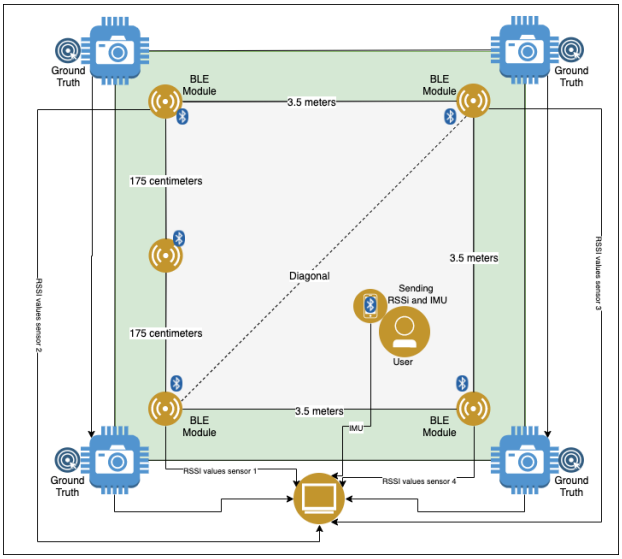



Fig. 1. Experiment setup for collection of IoT-TD dataset.

of dynamic tracking via BLE sensors is affected by several factors including nonlinear fluctuation of RSSI values and orientation of the device [16], [17]. These drawbacks have resulted in a surge of interest to develop hybrid (sometimes referred to as "Multiple-Model" or "Mixture of Experts") BLE-based estimation solutions achieved by combining more than one tracking model, e.g., coupled fingerprinting and Particle Filtering (PF) [18]; Integrated $K$-nearest neighbour ($K$-NN) and Support Vector Machines (SVM) [19]; Combined $K$-NN and trilateration, and; Cascaded Kalman Filter-Particle Filter (KFPF) are examples of recently proposed hybrid solutions. Pedestrian Dead Reckoning (PDR) [21], on the other hand, is an attractive alternative model due to significant advancements of Inertial Measurement Units (IMU) embedded within prevalent smart hand-held devices. While hybrid PDR for WiFi-based localization has been investigated, development of hybrid BLE and PDR models is still in its infancy.

**Contributions**: To address the aforementioned drawbacks, the paper first introduces a dataset, referred to as the IoT-TD, with ground truth consisting of synchronized RSSI and IMU measurements to pave the way for further reproducible research in this field, and secondly, develops a hybrid framework coupling RSSI-based tracking with PDR. More specifically, we target the following two key issues identified to be in the path of further advancement of BLE-based tracking approaches: (i) Lack of a unified dataset with precise ground truth for performing BLE-based tracking in indoor environments, and; (ii) Concentrated focus on utilization of stand-alone models and lack of attention to multiple-modeling. To address these gaps, at one hand, we introduce a real dataset, leveraging specific set of four optical cameras providing ground truth tracking trajectories with millimeter accuracies. The introduced dataset consists of RSSI values collected from five BLE sensors associated with different indoor continuous target tracks together with synchronized IMU measurements obtained from the target's hand-held device. Furthermore, the paper introduces a hybrid (multiple-model) dynamic estimation algorithm by fusion of an RSSI-based coupled KF and PF framework with IMU-based PDR tracking.

Fig. 2. Data collection setup.

The reminder of the paper is organized as follows: Section II presents the IoT-TD dataset. Section III presents the proposed hybrid (multiple-modeling) framework developed based on the IoT-TD dataset. Tracking results are presented in Section IV. Finally, Section V concludes the paper.

## II. The Prepared Dataset

Given the recent surge of interest on location-based services via BLE beacons, lack of a dataset with ground truth (actual labels) can be a significant obstacle for advancement of BLE-based indoor tracking/localiztion algorithms and research reproducibility. The paper takes a first step towards this goal and introduces the IoT-TD dataset, where the "Ground Truth Trajectories" are recorded in a synchronized fashion with the RSSI values together with IMU sensor measurements obtained, synchronously, from the moving target's hand-held device. All three components of the dataset are time-stamped and pre-processed being available publicly [26] for future BLE and PDR tracking algorithmic developments.

### A. Experiment Setup

The experimental environment used to construct the IoT-TD dataset is a 3.5 meters to 3.5 meters area (as shown in Fig. 1). Five BLE modules are used together with the built-in IMU sensor measurements of the user's mobile device, recorded synchronously with RSSI values. The goal is construction of a dataset for potential development of multiple model solutions, e.g., to fuse IMU data and multi-sensor RSSI signals to more accurately localize the user within the surveillance area. The following three different tracking scenarios are implemented to gather RSSI values via BLE beacons, IMU measurements from the mobile device, and ground truth trajectories via the Vicon system: (i) *Rectangular Walking*, where the user walks constantly on the sides of the rectangular area on a pre-defined path; (ii) *Diagonal Walking*, where the target walks along the diagonals of the area with constant velocity, and; (iii) *Random Track*, where the user walks randomly inside the surveillance region. During these scenarios, all the 5 BLE modules, 4 Vicon Vera cameras, and the smart phone IMU application are running and the collected data is saved synchronously. The rectangular and the diagonal movements (Scenarios (i) and (ii)), are more rhythmic, therefore, constitute easier scenarios. The random movement within the venue, on the other hand, can be considered as a more challenging tracking task.

The IoT-TD dataset collected through 75 data gathering sessions, 25 of which are prepared for Scenario (i), 25 sessions are devoted to Scenario (ii), and 25 Sessions are performed collecting data for Scenario (iii). In each session, the time-stamped RSSI data from five BLE modules, IMU data from the user's phone built-in sensors, and related Ground Truth of the user's phone are collected. In other words, during each tracking epoch, the RSSI values received from the five BLE modules across the designed environment are captured. At the same time, the IMU sensor data consisting of 9 different parameters are saved, simultaneously. Finally, the true flight position of the user consisting of 6 different components, i.e., three dimensional position data, and three rate of angular velocity (pitch, roll, and yaw) are gathered/preprocessed in the offline mode. Availability of precise reference dataset provides a unique opportunity for further development of BLE-based indoor tracking algorithms.

### *B. Construction of the Ground Truth*

In order to have access to the in-time exact location of the user in the series of tracking experiments, it is critical to provide the most accurate ground truth. In construction of the IoT-TD dataset, the Vicon Vero cameras (VICON Blade, VICON Motion Systems, UK) as shown in Fig. 2 are used, which are specific optical cameras making it possible to track/localize a user with millimeter accuracies. More specifically, state-of-the-art Vicon motion capture system containing four Vicon Vero infrared 1.3 megapixel cameras with sampling rate of 100Hz is used. Vicon DataStream SDK specially Vicon Tracker v.3.7 is used for constructing the ground truth trajectories. The provided on-board sensors on the Vicon Vero cameras are used to monitor the camera position for controlling their performance to guarantee accuracy of the given position. As the ground truth data collected via the Vicon Vero cameras plays a metric role in acknowledging the accuracy of an implemented tracking algorithm, we have calibrated the cameras for every data gathering session. The constructed dataset together with its description can be accessed freely [26]. The files associated with the ground truth of the user's phone consist of the time-stamped position of the user in 3 dimensions $(X, Y, Z)$, and also the rate of angular velocity (pitch, roll, and yaw). This completes introduction of the constructed IoT-TD dataset.

## III. PDR AND RSSI-BASED MULTIPLE-MODEL TRACKING

In this section, we use the constructed IoT-TD dataset introduced in Section II and design a Multiple-Model (MM) tracking framework (via estimation fusion) that combines the estimates obtained from RSSI values with those computed based on a PDR approach. A 2-D indoor tracking problem is formed with a single user walking within the surveillance region equipped with $N_b = 5$ number of BLE sensors. The following non-linear state-space model is considered

$$\boldsymbol{x}_k = \boldsymbol{f}\big(\boldsymbol{x}_{k-1}\big) + \boldsymbol{w}_k \tag{1}$$

$$\text{and} \quad \boldsymbol{z}_k = \begin{bmatrix} Z_k^{(1)} \\ \vdots \\ Z_k^{(N_b)} \end{bmatrix} = \underbrace{\begin{bmatrix} h^{(1)}(\boldsymbol{x}_k) + v_k^{(1)} \\ \vdots \\ h^{(N_b)}(\boldsymbol{x}_k) + v_k^{(N_b)} \end{bmatrix}}_{\boldsymbol{h}(\boldsymbol{x}_k)+\boldsymbol{v}_k}, \tag{2}$$

where $\boldsymbol{z}_k \in \mathbb{R}^{N_b}$ denotes the sensor's measurement vector at iteration $k$; $\boldsymbol{x}_k = [X_k, \Delta X_k, Y_k, \Delta Y_k]^T \in \mathbb{R}^4$ denotes the state vector (2-D location of the target) and their associated rate $\Delta \boldsymbol{X}_k$ and $\Delta \boldsymbol{Y}_k$; functions $\boldsymbol{f}(\cdot)$ and $\boldsymbol{h}(\cdot)$, respectively, are the state and observation models; terms $\boldsymbol{w}_k$ and $\boldsymbol{v}_k$ represent uncertainties and are assumed to be mutually uncorrelated white Gaussian noises.

**RSSI-based Coupled Kalman and Particle Filtering**: The initial step of the proposed MM algorithm is smoothing the fluctuations in the RSSI values with a KF-based algorithm. In this regard, the RSSI values obtained from the $j^{\text{th}}$ active BLE beacon, for $(1 \leq j \leq N_b)$, are modeled as

$$Z_k^{(j)} = \underbrace{-10\, N\, \log(\frac{D_k^{(j)}}{D_0}) + C_0}_{h^{(j)}(\boldsymbol{x}_k)} + v_k^{(j)}, \tag{3}$$

where $D_k^{(j)} = \sqrt{(X_k - X_k^{(j)})^2 + (Y_k - Y_k^{(j)})^2}$ with $\boldsymbol{x}_k^{(j)} = [X_k^{(j)}, Y_k^{(j)}]^T$ denoting 2-D location of the $j^{\text{th}}$ sensor; $D_0$ is the reference distance; $C_0$ is the average RSSI value at reference distance; $N$ is the pathloss exponent, and; the overall observation vector is constructed as $\boldsymbol{z}_k = [Z_k^{(1)}, \ldots Z_k^{(j)}, \ldots Z_k^{(N_b)}]^T$. To formulate the KF, an intermediate state vector $\boldsymbol{y}_k \in \mathbb{R}^{N_b}$ is defined, which models the smoothed RSSIs based on $\boldsymbol{y}_k = \boldsymbol{y}_{k-1} + \boldsymbol{\nu}_k$ as the state-model. The measured RSSI values $\boldsymbol{z}_k$ are used as the input observation to the KF with $\boldsymbol{z}_k = \boldsymbol{y}_k + \boldsymbol{u}_k$ as the observation model. Terms $\boldsymbol{\nu}_k$ and $\boldsymbol{u}_k$ are zero-mean Gaussian uncertainties used in the smoothing model with their second-order statistics ($\boldsymbol{Q}_{\text{RSSI}}$ and $\boldsymbol{R}_{\text{RSSI}}$) being learned through an initial calibration phase. The output of the KF models the smoothed RSSI vector [18].

After smoothing the RSSI values, Particle Filtering (PF) is used to estimate the location of the user $(\hat{X}_k, \hat{Y}_k)$ via a constant velocity dynamic model [23], [24] to represent the evolution of the constructed state vector over time. The observation model for implementation of the PF is the pathloss model in Eq. (3). The PF approximates the filtering distribution $P(\boldsymbol{x}_k|\boldsymbol{z}_k)$ using a set of $N_p$ particles $\{\mathbb{X}_k^i\}_{i=1}^{N_p}$ and their associated normalized weights $W_k^i$. Please refer to Reference [25] for further details.

**Pedestrian Dead Reckoning**: Among different algorithms to track a user in an indoor environment, PDR approach is one of the most convenient methods for which IMU is responsible for reporting inertial information of user's hand-held device. Basically, IMU sensors designed in smartphones consist of 3-axis accelerometer, 3-axis gyroscope, and 3-axis magnetometer. Raw data from the IMU is recorded by a developed swift application, which are then fed to a pre-processing unit responsible for smoothing the accelerometer, gyroscope, and magnetometer data and also calibration of the

magnetometer. Based on the analysis of the IMU sensors, we noticed that the most energies of the signal exists below 15Hz. Therefore, the raw data from IMU sensors are sent through a Butterworth low pass filter with a 15Hz cut-off frequency. Moreover, the magnetometer in the smartphones is prone to large measurement errors and can easily be distorted as a result of hard-iron and soft-iron interferences. As the magnetometer's data is of great value when determining the heading of a user in an indoor environment, this unit is considered as a critical step for every PDR-based localization approach. Here, we have adopted least square fitting ellipsoid method [22] to calibrate the magnetometer's raw data.

As stated previously, the magnetometer's data should be calibrated prior to any further steps such as heading detection, pitch, yaw, and roll calculations. In this regard, after passing the magnetometer's data through the pre-possessing unit to eliminate the soft iron and hard iron effects, calibrated magnetometer's data is used to determine yaw angle. In the user's walking scenario, yaw angle is considered as the heading ($\theta$) of the user. Therefore, for a random walk trajectory, data set is divided into small subsets, for each of which one can determine the heading ($\theta_k$) associated with that particular step as follows

$$\theta_k^{\text{Deg}} = Yaw_k^{\text{Rad}} \times 180/\pi \quad (4)$$

$$X_k = X_{k-1} + SL \times \cos(\theta_k) \quad (5)$$

$$Y_k = Y_{k-1} + SL \times \sin(\theta_k) \quad (6)$$

where $SL$ shows the Stride Length of user and assumed to be fixed during the iterations. Term $\theta_k$ is the orientation of the user estimated from magnetometer signals received from the user's phone. Based on Eq. (6), the 2-D location of the user $\boldsymbol{x}_k = [X_k, Y_k]^T$ at Step $k$ is calculated recursively based on its previous location at iteration $(k-1)$ and phone's orientation at step $k$.

**Fusion Strategy**: As we have two sets of state estimates obtained independently based on the RSSI-values and the IMU signals, we consider state estimation fusion [23], [24]. In this regard and by assuming that the two estimates are independent, the following fusion rule is used with the focus on the location calculated by the RSSI component

$$\hat{\boldsymbol{x}}_{k,1}^{\text{Fused}} = \boldsymbol{x}_k^{\text{RSSI}} + \boldsymbol{w}^{\text{RSSI}} \boldsymbol{\Sigma}_k^{\text{RSSI}} \left(\boldsymbol{\Sigma}_k^{\text{RSSI}} + \boldsymbol{\Sigma}_k^{\text{PDR}}\right)^{-1} \left(\boldsymbol{x}_k^{\text{PDR}} - \boldsymbol{x}_k^{\text{RSSI}}\right), \quad (7)$$

where $\hat{\boldsymbol{x}}_{k,1}^{\text{Fused}}$ is the minimum mean square error (MMSE) estimate of the RSSI-based fused estimates. Term $\boldsymbol{\Sigma}^{\text{RSSI}}$ is the covariance matrix associated with RSSI-based estimate $\boldsymbol{x}_k^{\text{RSSI}}$, while Term $\boldsymbol{\Sigma}^{\text{PDR}}$ is the covariance matrix associated with the PDR-based estimate $\boldsymbol{x}_k^{\text{PDR}}$. The term $\boldsymbol{w}^{\text{RSSI}}$ is the weight of influence of the RSSI-based tracking in this phase of fusion. We have also constructed a second fused estimate with the focus on the PDR estimate, i.e.,

$$\hat{\boldsymbol{x}}_{k,2}^{\text{Fused}} = \boldsymbol{x}_k^{\text{PDR}} + \boldsymbol{w}^{\text{PDR}} \boldsymbol{\Sigma}_k^{\text{PDR}} \left(\boldsymbol{\Sigma}_k^{\text{PDR}} + \boldsymbol{\Sigma}_k^{\text{RSSI}}\right)^{-1} \left(\boldsymbol{x}_k^{\text{RSSI}} - \boldsymbol{x}_k^{\text{PDR}}\right), \quad (8)$$

where $\hat{\boldsymbol{x}}_{k,2}^{\text{Fused}}$ is the Minimum Mean Square Error (MMSE) estimate of the PDR-based fused estimates. Term $\boldsymbol{\Sigma}^{\text{PDR}}$ is the covariance matrix associated with PDR-based estimate $\boldsymbol{x}_k^{\text{PDR}}$, while Term $\boldsymbol{\Sigma}^{\text{RSSI}}$ is the covariance matrix associated with the RSSI-based estimate $\boldsymbol{x}_k^{\text{RSSI}}$. Term $\boldsymbol{w}^{\text{PDR}}$ is the weight of influence of the PDR-based tracking in the fusion phase. To improve the tracking accuracy, the following final fusion rule is utilized

$$\hat{\boldsymbol{x}}_k^{\text{Fused}} = \boldsymbol{w}_{f1}^{\text{RSSI}} \hat{\boldsymbol{x}}_{k,1}^{\text{Fused}} + \boldsymbol{w}_{f2}^{\text{PDR}} \hat{\boldsymbol{x}}_{k,2}^{\text{Fused}} \quad (9)$$

where $\hat{\boldsymbol{x}}_k^{\text{Fused}}$ is the minimum mean square error (MMSE) estimate of the fused estimates of the whole system. Term $\boldsymbol{w}_{f1}^{\text{RSSI}}$ is the final fusion weight which is applied on the MMSE estimate of the RSSI-based fused estimates, and $\boldsymbol{w}_{f2}^{\text{PDR}}$ is the final fusion weight applied on the MMSE estimate of the PDR-based fused estimates. This completes description of the proposed MM framework based on RSSI and IMU measurements. Next, experimental results evaluated across the ground truth are provided.

## IV. Experimental Results

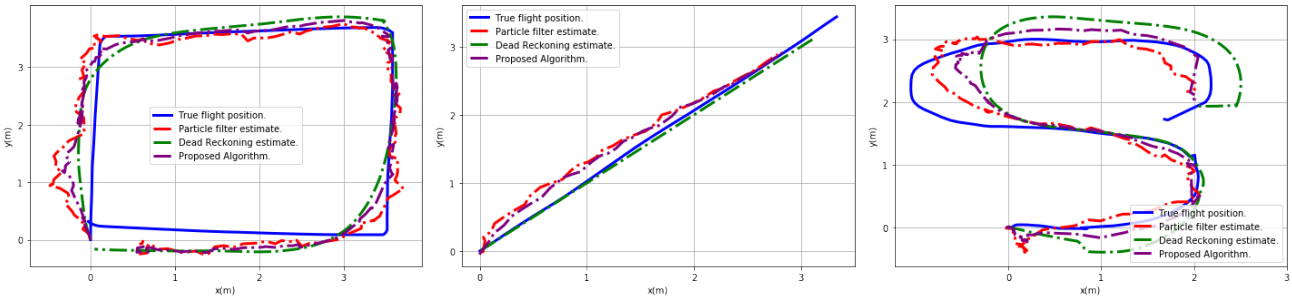
In existing IoT dynamic tracking applications, to the best of our knowledge, the real location of a user moving within the indoor environment is considered to be in specific pattern and was ideally estimated without fair comparison against the ground truth. This assumption, inherently, has a default error associated with it as the real location of the user is assumed. In this section and using the constrcuted IoT-TD dataset, we present RSSI-based estimates computed via coupled KF-PF tracking algorithm, together with the PDR-based tracking estimates and their fusion. The ground truth dataset, described in Section II, is used to evaluate accuracy of tracking algorithms.

Fig. 3 shows the three tracking scenarios together with the estimated trajectories obtained based on the coupled KF-PF tracking algorithm, PDR-based tracking, and the fusion algorithm. As it can be observed, the KF-PF tracking algorithm outperforms the PDR model in estimating the real position of the user, which is shown with "blue color" (obtained from the Vicon system). However, the variance of the KF-PF tracking estimates is radically higher than that obtained from the PDF model due to the RSSI fluctuations. Furthermore, as can be seen, fusion of the two models leads to a more accurate trajectory as expected.

Table I shows the Mean Squared Error (MSE) results based on the proposed MM fusion framework. As can be seen, the MSE values (in meter) are relatively small showing great potentials of the proposed hybrid solution. In the third phase of the fusion, which is combination of the RSSI-based fusion and PDR-based one, the accuracy of the model is better than stand alone fusions. It should also be mentioned that increasing the number of particles ($N_p = 200$ is used here), might improve the accuracy but comes with the cost of extra computation overhead. Number of particles in a real time scenario is a vital factor to avoid unacceptable latency, therefore, justifying the need for state estimation fusion with the PDR estimates.

## V. Conclusion

Aimed to prepare a BLE dataset with precise ground truth for performing reproducible research on indoor dynamic




(a) (b) (c)

Fig. 3. Estimated traget trajectories. (a) Rectangular track. (b) Diagonal scenario. (c) random scenario. (d) Similar to (a) with fusion track.

TABLE I
THE MSE RESULTS BASED ON THE IOT-TD DATASET COMPARED AGAINST THE GROUND TRUTH (COLLECTED WITH THE VICON SYSTEM) AND THE PROPOSED MULTIPLE-MODEL (HYBRID) FUSION FRAMEWORK.

| scenario | RSSI | PDR | FusI | FusII | FusIII |
|---|---|---|---|---|---|
| Rectangular | 0.1299 | 0.2111 | 0.1465 | 0.1584 | 0.1261 |
| Diagonal | 0.1961 | 0.2946 | 0.2729 | 0.479a | 0.1160 |
| Random | 0.1450 | 0.1740 | 0.1767 | 0.2387 | 0.1449 |

state estimations within IoT applications, the paper introduces the IoT-TD dataset and implements a multiple-model fusion framework to accurately track a user within an indoor environment. The introduced IoT-TD dataset leverages specific set of four optical cameras providing ground truth for indoor tracking with millimeter accuracies. The dataset also contains RSSI values collected from five BLE sensors together with synchronized IMU signals from the target's mobile device. Furthermore, the paper presents a multiple-model (hybrid) estimation framework, which couples a RSSI-based integrated Kalman and particle filtering approach with IMU-based PDR via state estimation fusion.

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