KF-Loc: A Kalman Filter and Machine Learning Integrated Localization System Using Consumer-Grade Millimeter-wave Hardware

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***Abstract*—With ever-increasing demands of e-commerce the need for smarter warehousing is increasing exponentially. This requires industry automation beyond Industry 4.0. In this work, we use consumer-grade millimeter-wave (mmWave) equipment to enable fast, and low-cost implementation of our localization system. However, the consumer-grade mmWave routers suffer from coarse-grained channel state information due to cost-effective antenna array design limiting the accuracy of localization systems. To overcome these challenges, we present a Kalman Filter (KF) and Machine Learning (ML) integrated localization system (KF-Loc). Where the ML model learns the complex wireless features for predicting the static position of the robot. When in dynamic motion, the static ML estimates suffer from position mispredictions that results in loss of accuracy. To overcome the loss in accuracy, we design and integrate a KF to enhance the accuracy of localization for moving robots. The KF learns the dynamics of the robot's motion to provide a smooth and highly accurate localization and tracking. Our system achieves centimeter-level accuracy for the two warehouse aisles with RMSE of 0.35m and 0.37m respectively. Further, compared with ML only localization systems we achieve significant reduction in RMSE by 28.5% and 54.3% for two different test aisles respectively.**

***Index Terms*—60GHz, indoor localization, kalman filter, machine learning.**

I. Introduction

In the recent decade, the advances in industry automation has gained a lot of attention from academia and industry. This has led to the evolution of the fourth industrial revolution, known as Industry 4.0 [1]–[3]. The advances are made in the computation and the communication aspects of the industry automation targeting the robotics and material handling. Figure 1 illustrates different technological components required for such automation. Realizing Industry 4.0 requires the design of autonomous robots working in coordination to perform various tasks. One of the preliminary requirements for the robot is to localize itself within the environment with very high accuracy for coordination and carrying out tasks. To perform the localization, information from various kinds of sensors can be used. Sensors such as LiDAR, vision and wireless are most commonly used for localization [4]–[7].

In the recent years, with the maturity of consumer-grade sensor technology, localization algorithms are heavily studied. However, reliable localization is still challenging for accurate and reliable autonomous design. This is due to the unpredictable environmental conditions for both indoor and outdoor applications. Table I summarizes the localization performance using different sensor modalities namely, Global Positioning System (GPS), LiDAR and vision. Using these sensors, Simultaneous Localization and Mapping (SLAM)-based localization approach can be applied and depending on the environment, reasonably good accuracy can be achieved. The LiDAR-based SLAM approach as well as vision-based systems are computationally very expensive as the data generated is either a point cloud of all the distances or video streams from hi-fidelity cameras respectively [7]. To alleviate these concerns, high performance computational devices such as Graphics Processing Units (GPUs) are needed on the robot to support the localization. While custom mmWave wireless equipment could be used as application specific wireless beacons but, designing such hardware at mmWave frequencies is significantly more challenging and is beyond the scope of this work. Further, to enable a low barrier to entry of automation for small-scale and local warehouses without compromising the accuracy and performance of the system we have introduced the use off the shelf mmWave routers.

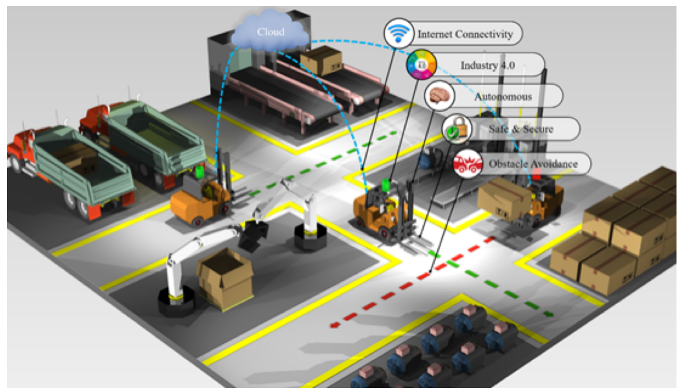

Fig. 1. Industry 4.0 automation and required technological components

In this work, we propose the use of consumer-grade off-the shelf 60 GHz wireless router for wireless localization in an indoor warehouse environment and design a Kalman Filter (KF) and ML integrated indoor wireless localization architecture, termed as *KF-Loc*. The ML model predicts the

TABLE I
PERFORMANCE COMPARISON WITH DIFFERENT WIRELESS BASED LOCALIZATION TECHNIQUES

Sensor	Performance	Advantages	Disadvantages
GPS	Around 10m	Low cost sensor off-the shelf localization	NLoS in indoor environment Significant loss in accuracy for indoor application
Camera [4]	Mean error of 0.75m	Low cost sensor High accuracy can be achieved	Susceptible to environment changes Require more complex localization system design
LiDAR [5]	0.07m to 0.03m RMSE	High Accuracy Obstacle avoidance ability	Computationally very expensive High cost sensor
UWB [6]	15cm RMSE	Low cost sensor Low power consumption	High dependence on sensor placement Need custom hardware design

static 2D position of the robot using the wireless features from 60 GHz millimeter-wave (mmWave) routers using a multi-layer neural network. The sensor features within the complex indoor warehouse environment is susceptible to loss of connection due to shadowing effects and obstruction due to objects and shelves. This can result in the loss of position information of the robot, especially when the robot is in motion. Further, due to robot's motion the ML output is susceptible to misprediction. As ML models are trained using static data and by itself cannot learn the robot's dynamics during motion. To overcome these challenges, KF is designed and integrated with the ML model. KF learns the motion behavior of the robot and combines it with the ML position output to provide highly accurate and smooth localization and run-time tracking of the robot.

II. Related Work

Indoor wireless localization at mmWave frequencies has been very active research area in literature and industries recently. One of the major contributing factor is the transition of various industrial sectors towards automation, which is regarded as next generation of industrial revolution, Industry 4.0. In this section, we discuss the recent work done in indoor wireless localization using mmWave wireless technology using machine learning and filtering approaches. For localization in indoor environments such as warehouses, wireless sensor based approaches are vastly investigated [8]–[11] and have been the preferred positioning approach for indoor environment due to the low cost, easy deployment and power efficiency. Wireless based localization techniques can be broadly classified into two technologies. First technique uses the channel propagation model to estimate the distance to the Client using the signal strength information and then using the known location positions of the APs and the distances, trilateration is used to predict the location of the Client. The second technique estimates the position of the Client by matching the known signal strength from the APs. This is done by collecting the signal strength information at many different locations within the environment and then using it as a database for matching. This technique is known as fingerprinting.

In [12], the authors present a moving average based k-Nearest neighbor approach for the fingerprint based localization. The accuracy achieved by their system is low. Machine learning and deep learning based approaches have been investigated for fingerprint based localization in recent years to provide high accuracy localization prediction. Authors in [13], [14] designed machine learning models like thors in [13], [14] designed machine learning models like and, support vector regression and support vector regression for localization using the received signal strength indicator (RSSI) fingerprinting as input features. In [15] authors proposed to use AP selection and data filtering approach to localize in an indoor environment. They show the improvement due to EM based filter and feature matching using Bayesian network. Authors in [16] have presented a deep reinforcement learning based framework for the indoor localization using Bluetooth devices. The idea is to mitigate the data collection step for training the ML model and use reinforcement based learning algorithms to learn the location predictions. Their approach shows low accuracy in testing by achieving Root Mean Square Error (RMSE) of 12.2m. In [17] authors have used same mmWave routers as ours for localization for indoor office environment and have shown accuracy of around 98.8% but in their work only 7 locations are used for the training and testing which is very coarse grained localization performance. Further in [17] the task of localization is static in nature as the robot is not in dynamic motion compared to our approach.

III. Localization Architecture

In our proposed architecture, we integrate ML localization model with the Kalman Filter, KF-Loc, to perform the run-time localization and tracking for the indoor autonomous robots. As ML predictions are static in nature and cannot learn the motion of the robot it makes the localization system less accurate due to mispredictions. In KF-Loc, the KF learns the dynamic behavior of the robot and combines it with the ML output in a prediction-update cycle to provide highly accurate localization performance. Figure 2 depicts the warehouse layout with the two aisles where we implement the localization system. Within the two aisles we have 68 distinct locations at which we collect the SNR features at the client. We have considered two

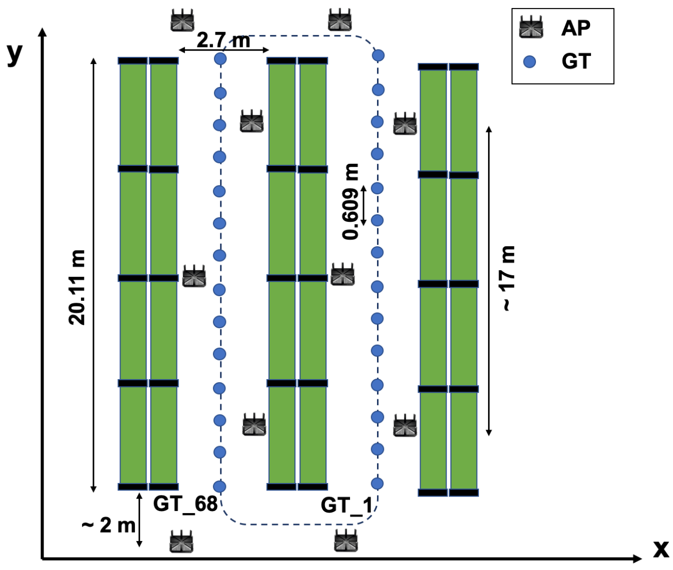

Fig. 2. Warehouse layout with two aisles for our system evaluation

aisles in our design, this is to show the effectiveness of our localization system to learn the complex features in an indoor environment at a large scale. The system architecture is shown in Fig. 3. In our framework, the first step is the training of a ML model to predict the location of the robot. Next, KF is designed and the ML prediction output is integrated with the filter to provide more accurate indoor localization and 2D tracking. In the subsequent sections the data collection routine, ML model setup and KF design is discussed in detail.

A. Data Collection Setup

To build the dataset we collect the Signal-to-Noise Ratio (SNR) features within the two aisles of the warehouse. This dataset is used by the ML model to train their weights during the training stage. At each location the Client is programmed to scan for the SNR features from all available APs. This is done by interfacing the 60 GHz router in the client mode and then interfacing it with a computation unit that is present on the robot. Next, at each individual location multiple scans are recorded at the Client. Due to obstruction and shadowing effects of mmWave routers, at Client we can have missing sector features and this can cause our model to not generalize during the training and for unseen test data. To overcome the missing feature information we perform a mean substitution of for each missing feature as a pre-processing step before we train the ML model and this is shown as the data imputation block in Fig. 3.

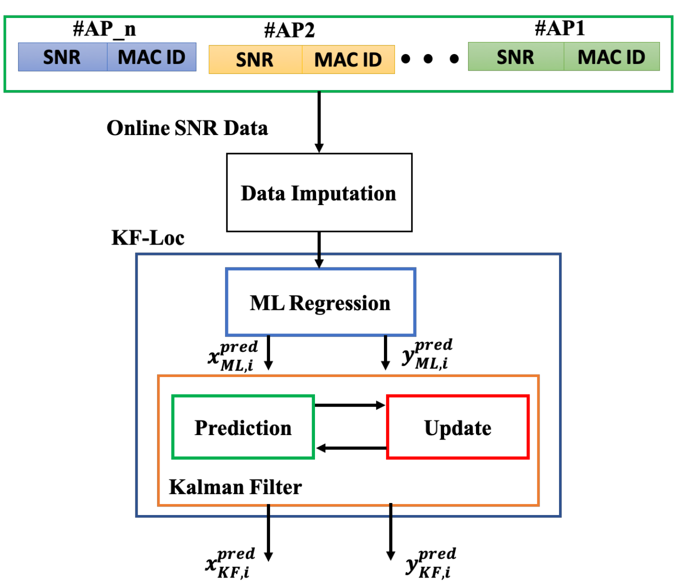

Fig. 3. Proposed kalman filter integrated machine learning architecture

Our training dataset is collected across different days and working hours. The rational behind collecting data across multiple days and multiple scans is to capture the random variations that occurs in the wireless signals across time and space. This routine makes the training data more feature rich and that significantly helps the ML models to generalize with high accuracy to unseen data during the test time. To test the trained models, another set of data is collected at same locations and during the testing, the ML models are fed only this test data and the model's output is the predicted location of the Client.

$$\hat{x_k} = Fx_{k-1} + Bu_{k-1} \tag{1}$$

$$\hat{P_k} = FP_{k-1}F^T + Q \tag{2}$$

$$y = z_k - H\hat{x_k} \tag{3}$$

$$S = H\hat{P_k}H^T + R \tag{4}$$

$$K = \hat{P_k}H^T S^{-1} \tag{5}$$

$$x_k = \hat{x_k} + Ky \tag{6}$$

$$P_k = (1 - KH)\hat{P_k} \tag{7}$$

B. Machine Learning Prediction Model

We train a regression-based ML localization model for the location prediction. The regression approach uses the outputs as the 2D coordinates of the robot within the warehouse. Here, the outputs of the neural network are continuous valued with two output heads. Training of the ML regression model is done by considering both x and y-dimension positions as the GT in the training dataset. The dataset consists of X_{fet} number of input features, where X_{fet} consists of SNR from all the sectors. The GT for each training sample is the known position location at which data collection is performed. Input dimension of our dataset is $N \times X_{fet}$, where N are the number of training data points. The dimension of GT in the dataset are $N \times 2$, as for each training sample we have position in two-dimension space on the warehouse floor.

C. Kalman Filter Design

Kalman filter estimates the state of a robot based on the prediction-update cycle. KF is a linear recursive estimator that minimizes the mean square error of the estimated parameters. In our design, we use the KF to track the position of the autonomous robot in a 2D space within an warehouse. The

TABLE II
PERFORMANCE COMPARISON WITH DIFFERENT ML MODELS

ML regression	Configuration	RMSE-X	RMSE-Y
LR	Linear Model	0.51m	2.60m
SVR	Polynomial kernel	0.71m	2.17m
MLP	**200, 200, 200**	**0.15m**	**0.91m**

input to the KF is the noisy position prediction output from the ML model i.e. (x,y) coordinates of the robot. The KF will filter the noisy coordinates to generate more accurate 2D tracking. First, the KF is initialized by setting up the various parameters. This includes setup of 60 GHz sensor's noise covariance matrix (R) and measurement matrix (H). Also, the robot's state vector (x), state transition matrix (F), and covariance matrix (P) are initialized. We assume the process covariance (Q) to be zero as we are performing a constant velocity based linear tracking of the robot.

In the first step, the KF performs the prediction of the robot's state and error covariance for the next time step, this is represented using (1), (2). Where, B and u are the control input matrix and control vector respectively due to the external and internal forces. Then in the next step, KF performs the update process where, based on the received measurements it updates the previously predicted state and covariance estimate. This is shown mathematically by (6), (7). It can be inferred that during the prediction stage, the uncertainty of the robot's position increases, as during this step no information is gained. While, during the update step we gain information through the measurements received from the sensors and we become more certain regarding the robot state.

KF considers the position probability of the robot to be Gaussian probability density function (PDF) which can be characterized by the mean and the standard deviation. The process starts by initializing the belief of the robot at the start time. For this, we take in our initial prediction output from the ML model. Next, using a motion model for the system, which is a constant velocity model in our design, we estimate the location of the robot in the next time step. During the update-cycle of KF, after the time step has elapsed, we obtain the measurement reading from the ML model and update our previously predicted belief of the robot's state. It is to note that the belief of the robot's position i.e. state and the measurements are modeled as Gaussian PDF. The tuning of R and Q parameters are done based on the sensor.

IV. EXPERIMENTAL EVALUATION

In this section, we provide detailed evaluation of the proposed KF localization framework. For the experimental testbed, we have selected a working warehouse [18] as shown in Fig. 4. Within the two aisles of the warehouse we have mounted ten 60 GHz routers on the ceiling configured as APs. The placement of the routers are done in a zig-zag manner. On the robot a 60 GHz router configured as Client is placed. For APs and Client, we have used TP-Link AD7200 routers. For the data collection routine, we collect the SNR data from all the available APs. We collect the training data within the two aisles by moving the robot 0.609m (2-feet) in the y-dimension of the aisle and keeping the x-dimension fixed. For both the aisles, we collect two different training datasets. For test-time evaluation, another separate held-out dataset is collected for the both aisles where total of 674 test samples are used to evaluate the system performance. In our work, the robot moves in one dimension within the aisle which in our experiments is the y-dimension for localization and tracking. This is realistic in many practical warehouses for autonomous agents, where only one agent is allowed to move in a single aisle at any given time and usually unidirectional motion is allowed [3].

Fig. 4. Warehouse aisle for experimental testbed

A. Machine Learning Model Analysis

The optimized ML localization model is a multi-layer neural network with three hidden layers consisting of 200 neurons each. The ML prediction is a regression model, where the output is the 2D prediction of the robot's position inside the warehouse. For model selection, we train and evaluate different regression models of varying complexity. The three model that we experiment with are Linear Regression (LR), Multi-Layer Perceptron (MLP), and Support Vector Regression (SVR). These ML models are considered as they represent

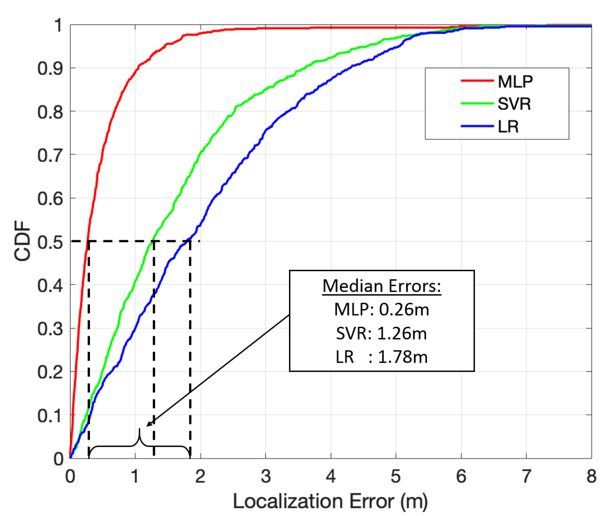

Fig. 5. Localization performance for different ML regression models

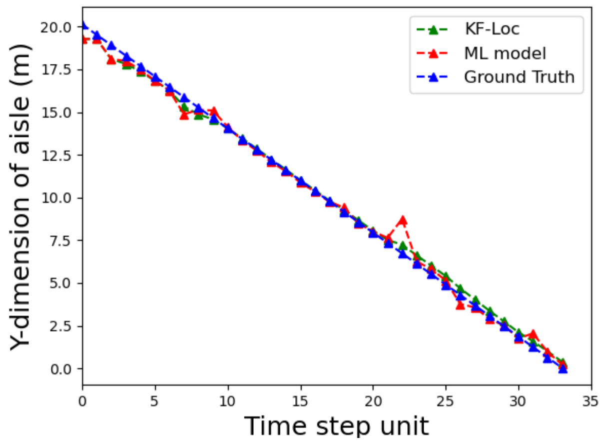

Fig. 6. Comparison of y-position between KF-Loc and ML model in aisle-1

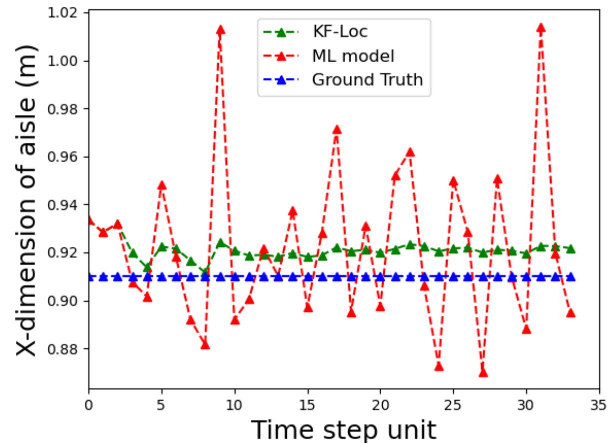

Fig. 8. Comparison of x-position between KF-Loc and ML model in aisle-1

the varying complexity in terms of computation and learning capability. We train and optimize each of the regression model individually on the training dataset and use the held-out test dataset to evaluate the performance.

Table II illustrates the performance of the three ML regression models. It is seen that for LR model has poor performance with Root Mean Square Error (RMSE) in y-dimension of 2.6m. This shows that using a simple and less complex learning model, the complex behavior of the 60 mmWave wireless features with distances cannot be learned at high accuracy and require the need of more complex learning models. SVR and MLP both more complex models achieves better performance compared to LR. But, it can be seen that MLP with three hidden layers and 200 neurons each, is able to achieve significantly higher accuracy with RMSE of 0.15m and 0.91m in x and y position respectively. Fig. 5 shows the localization error performance in terms of Cumulative Distribution Function (CDF) plot, where three different regression models are compared. It is seen from the figure that MLP also achieves the lowest median error of 0.26m when compared to the SVR and LR regression models. Based on these performance metrics we have selected the three layer MLP with 200 neurons each as our optimized ML localization model.

As mention, the robot only moves in y-dimension within the aisle but our ML model still predicts both the x- and y-position of the robot. This is required as the x-position of the robot will be different for different aisles and to differentiate the location of the robot within the multiple aisles 2D-position output is required. Next, we will analyze and describe how KF can overcome the fluctuations in position predictions and increase the accuracy of localization.

B. Kalman Filter Integrated Tracking

In our KF system, we define the robot state as a three-dimension vector defining the position in 2D Cartesian coordinate frame and its velocity in the y-dimension. The covariance matrix, P, is a 3x3 matrix initialized with very high uncertainty for velocity. The measurement matrix, H, is a 2x3 matrix, initialized with 1 for the position, and the measurement covariance, R, is a 2x2 matrix initialized with values 0.01. The ML prediction output is integrated with the KF to provide the 2D tracking. The optimized model designed in section IV-A is used as the ML model, which is MLP consisting of three hidden layers with 200 neurons each.

We evaluate the tracking of the robot in two different aisles of the warehouse. This is to evaluate the performance of the model in real world environment. Figs. 6 and 7 show

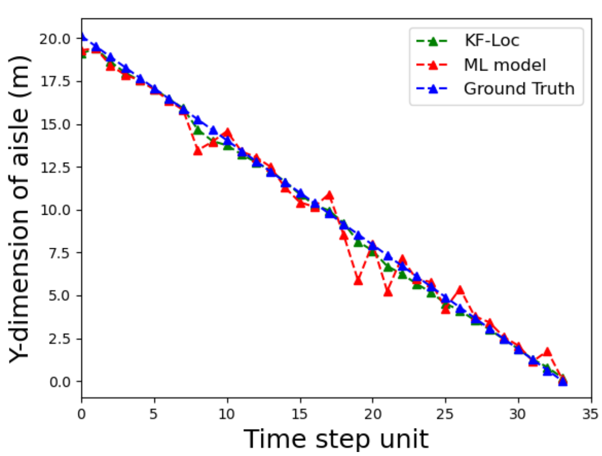

Fig. 7. Comparison of y-position between KF-Loc and ML model in aisle-2

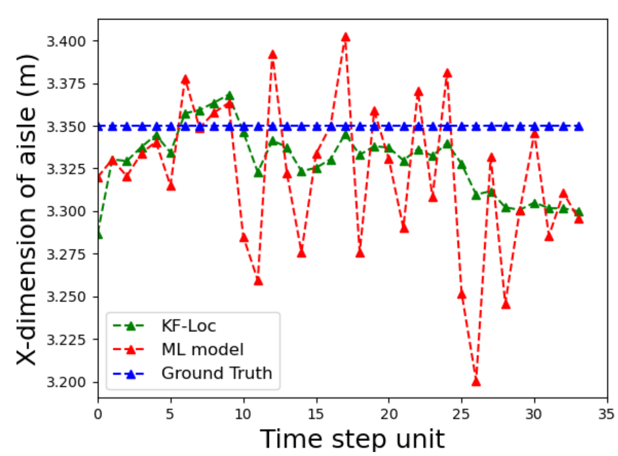

Fig. 9. Comparison of x-position between KF-Loc and ML model in aisle-2

TABLE III
PERFORMANCE COMPARISON WITH DIFFERENT WIRELESS BASED LOCALIZATION TECHNIQUES

Work	Wireless	Frequency	Environment	Methodology	Performance
Bahl [19]	RF-based	2.4 GHz	Indoor	KNN	2m-3m
Laoudias [20]	WiFi	2.4 GHz	Indoor	ANN	Mean error of 3.4m
Yang [21]	WiFi	2.4 GHz	Indoor	WiFi Fingerprinting	Mean error of 5.88m
Kanhere [22]	mmWave	28 GHz	Indoor	Fusion of AoA and received power	Mean error of 1.86m
Kanhere [22]	mmWave	28 GHz	Outdoor	Fusion of AoA and received power	Mean error of 34m
Bielsa [23]	mmWave	60 GHz	Indoor	Particle filter	Median error of 1.1m to 1.4m
Wei [24]	mmWave	60 GHz	Outdoor	DoA based WKNN fingerprint	Mean error 1.32m
Vashist [25]	mmWave	60 GHz	Indoor	MLP fingerprint	RMSE 0.84m
Our work	**mmWave**	**60 GHz**	**Indoor**	**KF and ML integrated (KF-Loc)**	**RMSE of 0.35m and 0.37m**

the performance comparison between the KF-Loc, in green, and ML model, in red, tracking in y-position for aisle-1 and aisle-2 respectively. The GT position is shown in blue for both the figures. It can be seen that the ML model produces fluctuations in the position estimates as the robot moves along the aisles. The fluctuations are due to the mispredictions by the ML model. These mispredictions are caused by the signal fluctuations at the Client due to the motion of the robot, resulting due to shadowing effects of the 60 GHz and obstructions between the Client and the APs [26]. Similarly, figs 8 and 9 shows the position estimates of the robot along the x-position within the aisle. Similar fluctuations are seen due to the dynamic motion of the robot causing mispredictions in the position prediction by the ML model. For location estimation in both the dimensions, KF-Loc system provides a lot smoother localization and tracking performance. This is seen as the KF within our KF-Loc system is able to filter and smooths out the raw position prediction from the ML model and capture the robot's dynamic motion by estimating it's velocity. This is where the KF provides a powerful integration with the ML model by estimating the robot's dynamic state variable, in our case the velocity, without explicitly being provided with velocity output from the robot. Thereby, providing a more robust and reliable run-time motion tracking.

The performance of KF-Loc is also compared with the ML

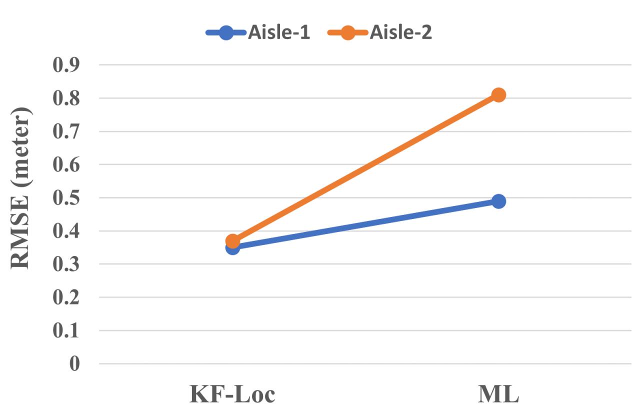

Fig. 10. Error comparison between KF-Loc and ML model in both the aisles

model by measuring the Root Mean Square Error (RMSE) of the robot in both the aisles individually. Figure 10 plots the robot's RMSE in y-position for both aisle-1 and aisle-2. For aisle-1, performance improvement with 28.5% reduction in RMSE error is achieved and for aisle-2, we see more significant performance improvement with 54.3% reduction in RMSE error. Also for both the aisles our system achieves centimeter level localization accuracy with RMSE of 0.35m and 0.37m respectively. In KF-Loc, the mispredictions in ML output position is reduced and improved by the KF by learning the motion dynamics of the robot, which is velocity in our case. This significantly reduces the effect of the wrongly estimated position of the robot by static ML model.

C. Comparison with Different Localization Approaches

In this subsection, we evaluate the performance of our localization system with different wireless localization methodologies. Table III illustrates the performance of our approach with other wireless based localization approaches. It is seen that our KF-Loc system achieves better performance in terms of localization accuracy, with RMSE error of 0.35m and 0.37m compared to different wireless localization techniques in more complex indoor environment. Further, it is seen form Table III that the mmWave based localization techniques achieves better performance compared to low frequency based WiFi techniques. This is because of the shorter wavelength of the 60 GHz band enables a higher resolution of the radio-map with richer features. Our 60 GHz based ML models outperforms the recent mmWave based localization systems proposed in [22]–[24] as our system integrates ML and KF predictions together to provide dynamic tracking and localization of the moving robot. We also show that compared to simple KNN [19] and LR based models, more complex ML models like MLPs are more efficient in learning the complex SNR features.

V. CONCLUSION

We have implemented a robust Kalman filter integrated machine learning based localization system, *KF-Loc*, for indoor warehouse using 60 GHz wireless routers. We introduce the use of the consumer-grade 60 Ghz wireless routers for providing high accuracy localization performance using off-the shelf mmWave routers. In our system, complex mmWave features are learned by regression based ML model, providing static position predictions of the robot. To improve the ML prediction error during the robot motion in run-time a Kalman filter is designed. The KF improves the motion tracking of the robot by removing the fluctuations due to mispredictions in ML output which are result of shadowing and small scale effects in mmWave channel resulting due to obstructions within the environment and robot's motion. The KF learns the robot's velocity without getting any explicit motion information from the robot. In this way, the KF-Loc system is able to provide run-time localization information compared to standalone ML based fingerprinting localization systems. To test practicality of our system we deploy and test our system within two aisles in a functional warehouse. The training data for the ML is collected over multiple days within the warehouse and a separate held-out test data is also collected for testing. Our KF-Loc system achieves centimeter-level accuracy in our test setup of two aisles with RMSE of 0.35m and 0.37m respectively. Further, when compared with static ML only localization system our proposed system shows significant performance improvement by achieving 28.5% and 54.3% improvement in RMSE error for the two test aisles respectively.

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