UHF RFID tag localization using pattern reconfigurable reader antenna

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***Abstract*—Passive ultra high frequency (UHF) radio frequency identification (RFID) tags have the potential to find ubiquitous use in indoor object tracking, localization, and contact tracing. We propose a machine learning-based method for RFID indoor localization using a pattern reconfigurable UHF RFID reader antenna array. The received signal strength indicator (RSSI) values (from 10,000 tags) recorded at the reader antenna units are used as features to evaluate the machine learning models with a train-test split of 75%-25%. The training and testing data is generated by a wireless ray tracing simulator. Five machine learning models: random forest regressor, decision tree regressor, Nu support vector regressor, k nearest regressor, and kernel ridge regressor are compared. Random forest regressor has the lowest localization error both in terms of average Euclidean distance (AED) and root-mean-square error (RMSE). For random forest regressor, localization error results show that 90% of the tags are within 1 meter of their true position, and 67% are within 50 cm of their true position based on Euclidean distance.**

***Index Terms*—Indoor localization, Internet of Things (IoT), machine learning, radio frequency identification (RFID), RFID reader antenna, reconfigurable RFID reader**

I. Introduction

Radio frequency identification (RFID) based indoor localization has significant potential in modern Internet of Things (IoT) infrastructures. Commercial RFID readers/interrogators are high-gain unidirectional circularly polarized antennas, primarily designed for tracking non-human objects. However, in recent years, research on on-body RFID sensors [1, 2] started to gain traction. Besides rethinking tag designs, reader antenna systems also need to adapt to the dynamic on-body scenarios. A pattern reconfigurable ultra high frequency (UHF) RFID reader antenna array [3] offers efficient interrogation of on-body sensors in a dynamic environment where one of the unit antennas would be selected for interrogation based on the location of the user. The multi-antenna arrangement opens the door to a new model of indoor localization using the received signal strength indicator (RSSI) fingerprint from the four reader antenna units, besides the traditional (geometrical) techniques such as trilateration, multilateration, *etc.* [4]. In this paper, we explore machine learning algorithms for the localization of passive RFID tags in a simulated indoor environment.

The existing body of work encompasses multi-reader, multi-reference tag-based RFID localization systems using different learning schemes (e.g., deep learning, clustering). Ni *et al.* proposed the LANDMARC system [5] based on the RSSI of active reference and target RFID tags. The proposed system adopts the k-nearest neighbor algorithm for localization. It uses k reference tags' location information to determine the target tags' location by weighting each of the k reference tags' coordinates. The LANDMARC system achieved a localization error of within 1 m for 50% of the target tags. Zhao *et al.* performed clustering of the reference tags and a target tag for each reader using k means clustering based on the backscattered signals' RSSI, and phase information [6]. The distances between the reader and the reference tags within the cluster are weighted to determine the target tag's distance from the reader. The linear least squares algorithm is then used to finalize the localization. Artificial neural networks (ANN) have proven to be very effective in different applications, and they have also been applied to RFID localization. Wang et al. [7] fused particle swarm optimization (PSO) and a back-propagation neural network to localize RFID tags. Soltani *et. al.* [8] used multi-layer ANN for localization. However, using neural networks for feature extraction requires feature-rich data, and one way to do that is to increase the dimensionality of the data. Mo *et. al.* [9] developed an antenna placement strategy sensitive to phase difference with position change. The RSSI and phase difference of the RFID tags were used to form higher-dimensional features to train a back propagation-support vector regression (BP-SVR) that achieves an average localization error of about 9.5 cm. Peng *et. al.* [10] used PDOA (phase difference of arrival) and RSSI to form higher-dimension images and performed localization through feature extraction using convolutional neural networks (CNN).

We simulated the indoor environment using electromagnetic ray-tracing software (Wireless InSite), including the reconfigurable reader antenna and passive RFID tags. Wireless channels simulated in ray-tracing software can be used to emulate [11] challenging environments, such as an intensive care unit or an infectious disease treatment facility, which is not feasible with real experiments. Using the reconfigurable reader antenna, we form an RSSI feature space for the RFID tags placed in the free space surrounding the reader. Machine learning models are trained using the RSSI feature space, that can predict the location of the RFID tags at unknown locations with an average localization error of about 47.69 cm.

II. Simulation Setup

A. Reconfigurable Reader Antenna Array

The reconfigurable reader antenna consists of four identical circularly polarized patch antennas (Fig. 1). An electrically controlled single-pole four-throw (SP4T) switch activates one

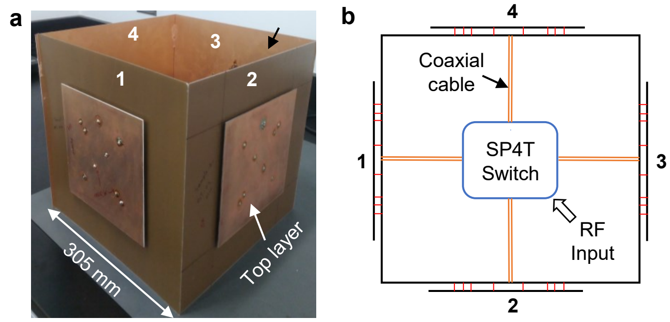

Fig. 1: a) Reconfigurable UHF RFID reader antenna array [3] prototype, and b) block diagram of the top view.

unit antenna at a time. Traditional single unit reader antennas are not suitable for on-body RFID sensors due to the reduction in radiation efficiency in the vicinity of the human body [12]. The reconfigurable reader antenna can select the optimum antenna based on the location of the tag/user. The maximum gain of each antenna is 8.9 dBi, covering the UHF RFID band (902-928 MHz). The four broadside directional beams can efficiently interrogate tags around the azimuth plane.

B. Proposed Method

We propose a technique for RFID localization based on a reconfigurable reader antenna array. Any RFID tag within the read range of the reader will have a unique RSSI signature recorded at the reader. The received power at the four antennas of the reader can be taken together to form the signature of an RFID tag. In Fig. 2, the RSSI recorded at the four reader antennas are R_1, R_2, R_3, and R_4 respectively. Thus the RSSI signature of the RFID tag is (R_1, R_2, R_3, R_4). Placing numerous RFID tags at known locations around the space of the reader and recording the RSSI signatures of each tag can be used to form a dataset. This dataset can be used to train a machine learning model able to determine the location of an RFID tag at an unknown location given its' RSSI signature. However, the success of such a learning-based model is highly dependent on the dataset. The more space covered, the better the model performance will be.

C. Simulation and Data Generation

The reconfigurable RFID reader antenna array and the passive RFID tags are simulated in the Wireless InSite ray-tracing software. The dimension of the room is 5 m $\times$ 5 m $\times$ 5 m where the reader antenna is placed at the center of the XY plane. The reader and the tags are placed 1 m above the ground. The material of the walls, floor, and ceiling is concrete. Four left-hand circular polarized directional antennas represent the four antennas of the RFID reader, and the passive RFID tags are simulated as omnidirectional vertically polarized antennas. The diagonal pairs of the four reader antennas are placed 0.305 m apart to be consistent with the dimension of the reconfigurable RFID reader antenna array. To avoid near-field effects, the omnidirectional RFID tag antennas are placed at least 0.56 m (far-field distance of each reader antenna unit at 915 MHz) away from the reader antennas. Also, no tag is placed within 0.305 m of the walls. Considering the constraints, the effective area for placing the tags on the XY plane is 18.52 m^2. To place the tags evenly into different segments of the effective area, it is divided into four zones, and the tags are then placed randomly in the zones. The zones are selected in such a manner that the number of points per square meter for each zone is equal. To capture the entire scene, 10,000 tags were placed at random. Fig. 3 shows the number of tags in the four zones, and Fig. 4 shows the distribution of the tags. The simulation records the received power of each RFID tag at the four reader antenna units. Fig. 5 shows the simulated indoor environment with four tags and the reconfigurable reader antenna units.

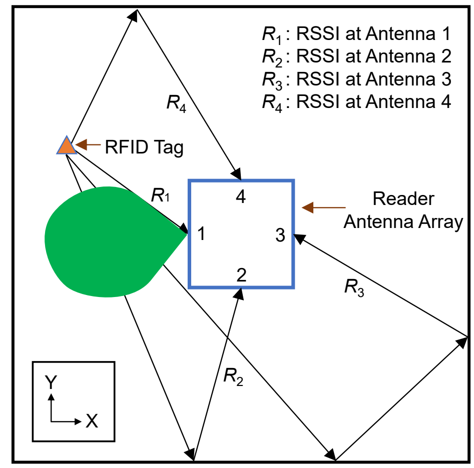

Fig. 2: RSSI fingerprints at the reader antenna. (Antenna 1 is active)

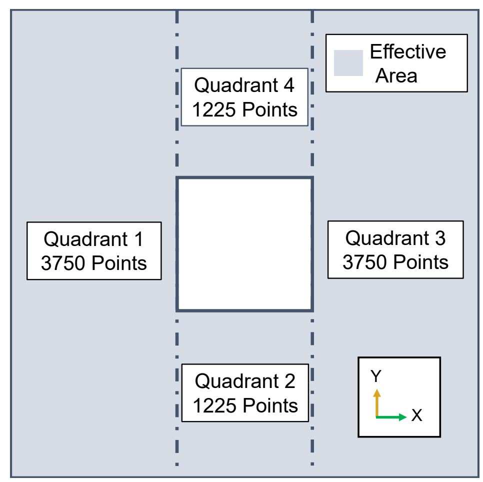

Fig. 3: Distribution of the RFID tags.

D. Dataset Description and Model Selection

The performance of any learning-based model is dependent on a good-sized, good-quality dataset. Different size of the dataset has been tested to determine the optimum size. However, considering the dimension of the simulated environment, simulation time in the ray-tracing software, and

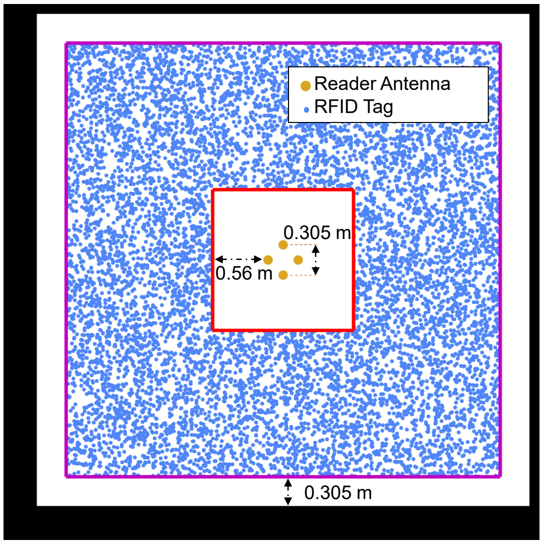

Fig. 4: Placement of the reader antenna and the tags.

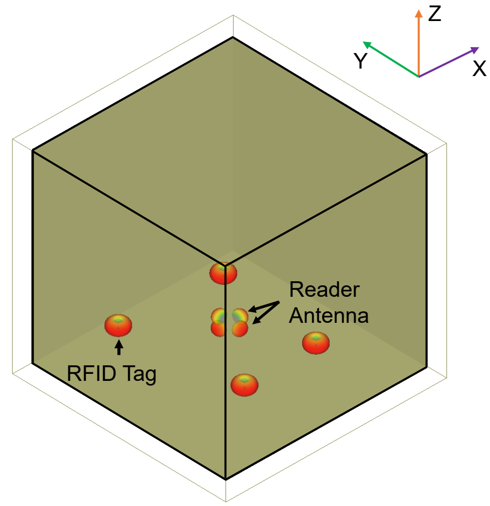

Fig. 5: Simulated indoor environment in ray-tracing software.

average localization error, a dataset of 10,000 samples has been selected for the final benchmarking. The dataset is a 10,000 $\times$ 4 dimensional matrix, where 10,000 is the number of RFID tags in the simulated environment. Each row of the matrix contains the received powers at the four reader antenna units for a particular tag. The dataset is labeled, and the labels are the $(x,\, y)$ coordinates of corresponding tags. The dataset is used to train machine learning models to perform multi-output regression [13]. The input to the regression models are RSSI signatures of the passive RFID tags, and the outputs are their $(x,\, y)$ coordinates. To determine the best regression models, a carefully designed grid search [14] process has been performed leveraging k-fold cross validation [14] where $k = 4$ with 10 repeats. While performing the grid search all the 10,000 data has been used. Five regression models were selected based on their average localization error. Average Euclidean distance (AED) and root-mean-squared error (RMSE) are used to calculate the average localization errors. The selected regression models are Random Forest, K Neighbors, Decision Tree, Nu Support vector, and Kernel Ridge regressor [14]. The parameters of the regressors are summarized in Table I.

TABLE I: Parameters of the regressors

Regressor	Parameters
Random Forest regressor	kernel = rbf, number of trees = 150, criteria = squared error, maximum number of features = square root of number of features
Decision Tree regressor	criteria = squared error, max depth = 10
K Neighbors regressor	K = 9, weights = distance, algorithm = kd tree
Nu Support Vector regressor	kernel = rbf, gamma = 0.01, nu = 0.95
Kernel Ridge regressor	kernel = rbf, gamma = 0.01, alpha = 0.1

III. Results and Discussion

We have tested different sized datasets randomly sampled from the total dataset of 10,000 samples. Each random sample of the dataset is then split into train set and test set with a percentage of 75% and 25% respectively. Given there is M number of tags in the test set and the coordinates of the tags are $(x_1, y_1), (x_2, y_2), \ldots.., (x_{\mathrm{M}}, y_{\mathrm{M}})$, and the corresponding predictions are $(\widetilde{x}_1, \widetilde{y}_1), (\widetilde{x}_2, \widetilde{y}_2), \ldots.., (\widetilde{x}_{\mathrm{M}}, \widetilde{y}_{\mathrm{M}})$, the AED is defined by Eq. 1, and RMSE is given by Eq. 2. Here, R is the number of repetitions for train-test split, training, and error calculation.

$$AED = \frac{1}{R}\sum \frac{\sum_{\mathrm{i}}^{M}\sqrt{(x_{\mathrm{i}}-\widetilde{x}_{\mathrm{i}})^2+(y_{\mathrm{i}}-\widetilde{y}_{\mathrm{i}})^2}}{M} \tag{1}$$

$$RMSE = \frac{1}{R}\sum\left(\frac{\mathrm{RMSE_X}+\mathrm{RMSE_Y}}{2}\right) \tag{2}$$

$RMSE_X$ and $RMSE_Y$ are the root mean square errors in X and Y axis predictions respectively. $RMSE_X$ and $RMSE_Y$ are given by:

$$\begin{aligned} RMSE_{\mathrm{X}} &= \sqrt{\frac{\sum_{\mathrm{i}}^{M}(x_{\mathrm{i}}-\widetilde{x}_{\mathrm{i}})^2}{M}} \\ RMSE_{\mathrm{Y}} &= \sqrt{\frac{\sum_{\mathrm{i}=1}^{M}(y_{\mathrm{i}}-\widetilde{y}_{\mathrm{i}})^2}{M}} \end{aligned} \tag{3}$$

From our experiments, we observe that more data gives better localization accuracy. Fig. 6 shows the relationship between average localization error and dataset size. The final benchmarking of the regression models is performed on the whole dataset of 10,000 samples with 7,500 data on the training set and 2,500 data on the test set. Table II summarizes the localization errors for all the five regression models.

Table II shows that the Random Forest regressor has better AED and RMSE than the rest of the regression models. Fig. 7 is the cumulative distribution of localization error for the random forest regressor. In terms of Euclidean distance, more than 90% of the tags fall within a localization error of 1 m while more than 67% of the tags are within an error of 50 cm.

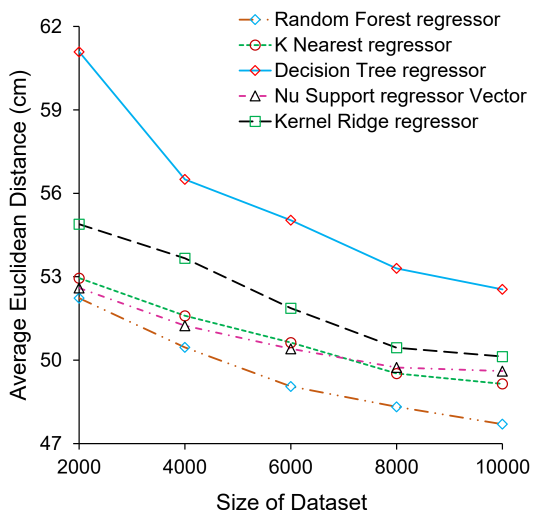

Fig. 6: AED *vs.* size of dataset

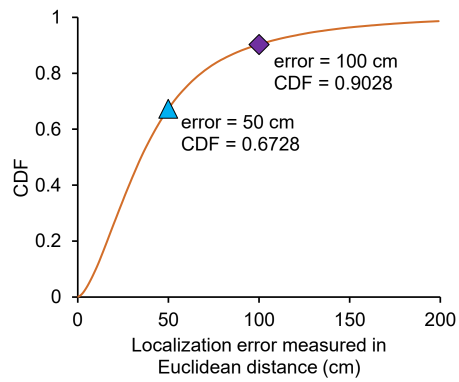

Fig. 7: CDF of error (Euclidean distance) for random forest regressor.

TABLE II: Errors of regression models

Regression Model	AED (cm)	RMSE (cm)
Random Forest	47.69	45.23
Decision Tree	52.24	51.15
K-Nearest	49.15	47.04
Nu Support Vector	49.61	47.43
Kernel Ridge	50.13	48.10

IV. Conclusion

This paper presents a novel machine learning-based RFID localization technique using a reconfigurable reader antenna array. The indoor environment is simulated in a ray-tracing software with 10,000 passive RFID tag locations and the reconfigurable reader antenna. A dataset is created using the RSSI fingerprints of the RFID tags on the reader antenna. Five machine learning regression models are compared using the dataset. Results show that, based on the Euclidean distance, 90% of the tags are within an error of 1 m, and 67% are within 50 cm error. In the future, we will study on-body RFID sensor localization using simulation, channel emulation, and field experimentation. Furthermore, the feasibility of deep learning algorithms will be studied by increasing the number of features with an additional reader antenna array.

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