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The Intuitive Supervision Model (ISM) using Convolution Neural Networks (CNN) and Unscented Kalman Filters (UKF)

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Abstract: Radio frequency identification technology is one of the fastest-growing technologies in the realms of navigation, medical, robotics, communication system, logistics, security, safety, etc. Surveillance is one of the important fields where high accuracy and fast response are needed. In this research work, RFID sensors are used to track moving objects with an intelligent supervision model. The sophisticated surveillance model employs neural networks followed by an adaptive filtering technique based on an Unscented Kalman filter. A neural network is also one of the most efficient and powerful technology in the field of learning and data processing capability. A neural network has the capability of processing a mammoth amount of data because of this feature its efficiency and accuracy are quite high. This model localizes N number of objects/targets through an intelligent surveillance model, picks a random object from this pool of localized objects to track, categorizes their movement through a controlled checkpoint, and calculates the distance traveled by the moving object /target. Experimental results show that the proposed model can locate multiple-objects with the help of multiple input RFID antennas and tags and track them concerning to the RFID antennas with high accuracy and stability in the complex indoor environment and this intuitive model can be effectively implemented at the airport, railway station, shopping mall, retail management, as well as any other surveillance purpose. For this research work number of authors work, is reviewed and based on literature review this model is designed.

Keywords: Adaptive Filtering, Convolution Neural Network (CNN), Deep Neural Network, Gauss-Newton Algorithm, Intelligent system, Indoor Positioning and tracking, Radiofrequency Identification (RFID), Unscented Kalman Filter (UKF), Received Signal Strength Indication (RSSI)

I. INTRODUCTION

Artificial Intelligence is one of the fastest-growing, efficient, and potential emerging technologies because of its efficiency and ability to perform extraordinarily. In this proposed work, an AI-based intelligent surveillance model is designed using CNN and UKF with the help of UHF RFID sensors.

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RFID is one of the admired and latent promising technologies in the turf of wireless sensing technology, communication system, confidentiality, and security because of its characteristics such as low power consumption, no line of sight requirement, cost-effective, fast identification, high precision made quite suitable for the surveillance of mobile objects in the indoor tracking scenario [1]-[7]. The idea of RFID localization traditionally relied on range-based mechanisms like time of arrival (TOA), time difference of arrival (TDOA), received signal strength indicators (RSSI), etc [8]-[9]. Their accuracy, however, does not match the requirements of the real-life environment. These traditional range-based approaches are limited in their capabilities to fully utilize data and localize massively deployed RFID tags. Due to the lack of ability to perform deep learning, with traditional fingerprinting-based algorithms, datasets are inherently clattered, making them inefficient. As a result, positioning accuracy can no longer be improved. In recent times, fingerprinting-based indoor localization has become a promising technology. The fingerprint database contains thorough measurements of the scene, and then to determine the position of an object, updated measurements are gathered and evaluated with data in the database. Several approaches to RFID localization have been presented that uses RSSI measurements to evaluate fingerprinting [10]-[12]. In this intelligent surveillance model, CNN is used because of its high precision and stability in real-time, multifarious indoor localization, also CNN has the capability of extracting and processing a bulky amount of data as well as training fingerprint features. With the help of the most popular and efficient UKF [13]-[16], this intelligent surveillance model has been designed. The conceptual model of the AI-based intelligent surveillance model is shown in figure 1.

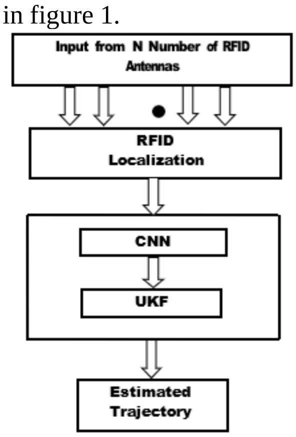

Figure-1: AI-based Conceptual Intelligence Supervision Model

Specifically, this research paper comprises RFID-based localization and the proposed intelligence model techniques in section II, the simulation results of this intelligent model are shown in section III. Finally, this proposed work will be wind up in segment IV.

II. CONCEPT OF AI-BASED SUPERVISION TECHNIQUES

A. UHF RFID Based Localization

1. The RSSI Measurement Model

A UHF RFID propagation model is presented in detail in this model. This logarithmic model can visualize the rapport between signal reception strength and distance of transmission. According to this model, the acknowledged power at a distance d [17] is

$$P_L(d) = P_L(d_o) + 10\, n \log (d/d_o) + \boldsymbol{X_\sigma} \quad (1)$$

In this equation, d represents the remoteness between the reader and the tag, do represents the reference distance, PL (d) describes the free space path loss and n represents an exponent of path loss. $\boldsymbol{X_\sigma}$ represents a Gaussian random variable with zero mean and variance σ2. The power is uttered in dBm and the distance in meters. $\boldsymbol{X_\sigma}$ is also known as shadow fading. The RSSI is given by

$$P_r(d) = P_t - P_L(d) \quad (2)$$

Where Pr (d) denotes the acknowledged power from the tag by the RFID reader at distance d, Pt denotes the transmitted power from the transponder [17].

The RSSI obtained by the reader is

$$P_L(d) = P_t - P_L(d_o) - 10\, n \log (d/d_o) + \boldsymbol{X_\sigma} \quad (3)$$

The strength of signal is measured by log-distance model of the reference RFID reader and an object.

Now, assume x and y be the location of the target along the horizontal axis and the longitudinal axis respectively. For simplicity velocity and acceleration of the target are omitted. $\boldsymbol{x(t_i)}$ ***and*** $\boldsymbol{y(t_i)}$ are the factual location coordinates of the target and $\boldsymbol{x_n(0)}$ and $\boldsymbol{y_n(0)}$ are the coordinates of the nth reader in the two-dimensional tracking space [1]

So the reduced condition (state) variable of the arrangement at time ti is

$$X(t_i) = [x(t_i) \quad y(t_i)] \quad (4)$$

$d_n(t_i)$ is the tangible distance between the nth tag and reader at the sampling time t_i

$$d_n(t_i) = \sqrt{\left(x(t_i) - x_n(0)\right)^2 + \left(y(t_i) - y_n(0)\right)^2} \quad (5)$$

$z_n(t_i)$ and $v_n(t_i)$ is the measured distance and measurement noise of the sampling time t_i

$$z_n(t_i) = d_n(t_i) + v_n(t_i) \quad (6)$$

The processing model beneath irregular sampling intervals is given below

$$x(t_i) = A(t_{i-1})\, x(t_{i-1}) + \omega(t_{i-1}) \quad (7)$$

Where,

$A(t_{i-1}) = \begin{bmatrix} A_x(t_{i-1}) & 0 \\ 0 & A_y(t_{i-1}) \end{bmatrix}$ and $A_x(t_{i-1})$ and $A_y(t_{i-1})$ is the state (conditional) transition matrix along the latitude axis and longitude axis respectively, the state transition matrix is assumed to be a unity that is

$$A_x(t_{i-1}) = A_y(t_{i-1}) = 1$$

$w(t_{i-1}) = [\omega_x(t_{i-1}) \quad \omega_y(t_{i-1})]^T$ is the processing noise in the latitude axis and longitude axis and these noises are sovereign of each other.

The covariance matrix is given by

$$Q(t_{i-1}) = \begin{bmatrix} Q_x(t_{i-1}) & 0 \\ 0 & Q_y(t_{i-1}) \end{bmatrix} \quad (8)$$

And the processing noise covariance matrix is assumed to be a unity that is $Q_x(t_{i-1}) = Q_y(t_{i-1}) = 1$

As for simplicity, we have omitted the parameters that are velocity and acceleration of the object, the system is reduced to position only. The state transition matrix and the processing noise covariance matrix are assumed to be unity.

2. The Proposed Localization Algorithm GAUSS-NEWTON Algorithm

For identification of the position of objects/targets, the Gauss-Newton algorithm is used and it is discussed in detail below.

Specified, m functions r = (r1……….r m) (frequently known as residuals) of n variables β = (β1………… βn) with m ≥ n, the Gauss-Newton algorithm method iteratively discovers the unknown value of the variables that reduce the sum of squares,

$$S(\beta) = \sum_{i=1}^{m} \boldsymbol{r_i(\beta)^2} \quad (9)$$

$\beta^{(0)}$ is the preliminary guess for the minimum

$$\boldsymbol{\beta^{(s+1)}} = \boldsymbol{\beta^{(s)}} - (\boldsymbol{J_r^T J_r})^{-1} \boldsymbol{J_r^T r} \left(\boldsymbol{\beta^{(s)}}\right) \quad (10)$$

In equation (4) r and β represents column vectors and their entries in the Jacobian matrix

$$(\boldsymbol{J_r})_{ij} = \frac{\boldsymbol{\beta r_i(\beta^{(s)})}}{\boldsymbol{\partial \beta_J}} \quad \mathbf{(11)}$$

Stipulation m = n, then iteration equation cut down to

$$\boldsymbol{\beta^{(s+1)}} = \boldsymbol{\beta^{(s)}} - (\boldsymbol{J_r})^{-1} \boldsymbol{r} \left(\boldsymbol{\beta^{(s)}}\right) \quad (12)$$

The above-simplified equation is a one-dimensional direct sweeping statement of NEWTON's method. The main aim is to discover the parameter β, so that the function f (x, β) finest hysterics some data points (x_i, y_i) in data fitting, and the function r_i is the residual

$$\boldsymbol{r_i(\beta)} = \boldsymbol{y_i - f(x_i, \beta)} \quad (13)$$

The GAUSS-NEWTON algorithm can be articulated in conditions of Jacobian matrix J_f of the function f as

$$\boldsymbol{\beta^{s+1}} = \boldsymbol{\beta^{(s)}} + \left(\boldsymbol{J_f^T \cdot J_f}\right)^{-1} \boldsymbol{J_f^T r} \left(\boldsymbol{\beta^{(s)}}\right) \quad (14)$$

Where $\left(\boldsymbol{J_f^T \cdot J_f}\right)^{-1} \boldsymbol{J_f^T}$ is the left pseudo inverse of J_f.

This condition is m ≥ n is necessary otherwise, $(\boldsymbol{J_r^T \cdot J_r})^{-1}$ is singular and the equation cannot be solved.

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The Gauss-Newton algorithm can to be linearly approximated by Taylor's series expansion

$$\boldsymbol{r}(\boldsymbol{\beta}) \approx \boldsymbol{r}\left(\boldsymbol{\beta}^{(s)}\right) + \boldsymbol{J}_r\left(\boldsymbol{\beta}^{(s)}\right)\boldsymbol{\Delta} \tag{15}$$

$$\text{Where, } \boldsymbol{\Delta} = \boldsymbol{\beta} - \boldsymbol{\beta}^{(s)} \tag{16}$$

$\boldsymbol{\Delta}$ Aims to lessen the sum of squared error

$$\boldsymbol{min}\left\|\boldsymbol{r}\left(\boldsymbol{\beta}^{(s)}\right) + \boldsymbol{J}_r\left(\boldsymbol{\beta}^{(s)}\right)\boldsymbol{\Delta}\right\|^2 \tag{17}$$

The above equation is the linear least-square dilemma, which can be solved unambiguously. With the help of this model, target location estimation has been done. To further explain this concept, the proposed flow chart of intelligent tracking model based on RFID localization is shown in figure 2.

B. PROPOSED INTELLIGENT MODEL TECHNIQUES

As shown in figure 1, an intelligent model comprises intelligent techniques i.e. CNN and UKF; this section of the paper discusses the theory of intelligent techniques.

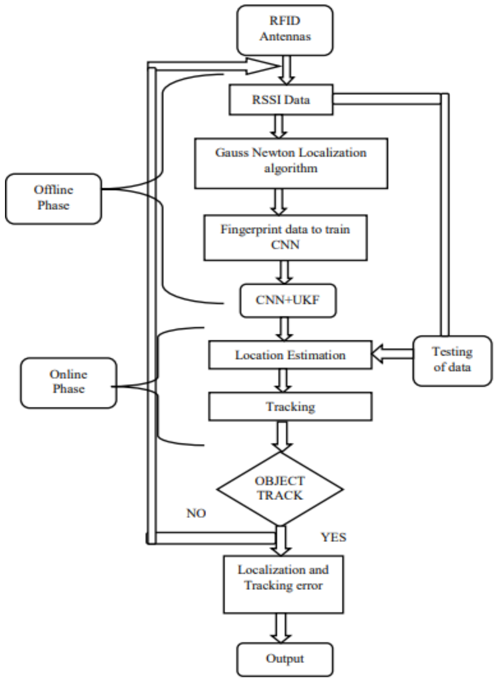

Figure-2: The Proposed Flow Chart of AI-based Intelligence Surveillance Model

1. Convolution Neural Network

In CNN architecture, a convolution layer is an elementary layer that performs the mining of features.

The kernel and weight values of the layer are then updated according to loss estimates on the training dataset through a back-propagation algorithm called gradient descent. The second layer of CNN architecture is a nonlinear activation function. The linear output of the convolution operation is used as input to the nonlinear activation function. In this work rectified linear unit (ReLU) was used to remove negative values (obtained during convolution) from the filtered images and replace them with zeroes. Next, the pooling layer reduces the dimensionality of the feature maps so that small shifts and distortions can be introduced, decreasing the learnable parameter. Following, a final convolution layer is a fully connected layer, where output feature maps are rehabilitated into a one-dimensional arrangement of vectors and then referred to as a fully connected layer [11], as shown in the block diagram of CNN architecture is shown in figure 3.

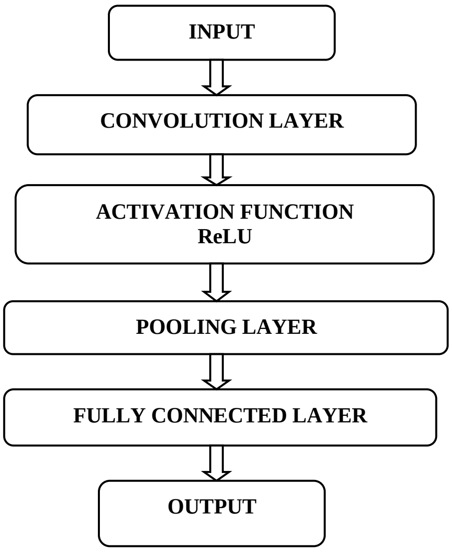

Figure-3: Block Diagram of CNN

2. UKF Based Tracking [1]

The position estimation of the trajectory is contemplated adaptively, for this purpose Unscented Kalman filter is considered

A generalized sigma point method is applied here

$$x_a^{(0)} = \left[x_x^{(0)} \quad x_w^{(0)} \quad x_v^{(0)}\right]^T$$

$$= \left[\hat{x}(t_{i-1}/t_{i-1}) \quad 0_{n_w} \quad 0_{n_v}\right]^T \tag{18}$$

Where 0_{n_w} and 0_{n_v} are the columns vectors of zeroes and the dimensions of the processing noise and the measurement noise are the same

$$x_a^{(i)} = \left[x_x^{(i)} \quad x_w^{(i)} \quad x_v^{(i)}\right]^T$$

$$= x_a^{(0)} + \sqrt{P_a(t_{i-1}/t_{i-1})(\lambda + L)} \tag{19}$$

Where i = 1,2,3……..L

$$x_a^{(i+L)} = \left[x_x^{(i+L)} \quad x_w^{(i+L)} \quad x_v^{(i+L)}\right]^T$$

$$= x_a^{(0)} - \sqrt{P_a(t_{i-1}/t_{i-1})(\lambda + L)} \tag{20}$$

Where i = 1, 2, 3……..L

$$P_a(t_{i-1}/t_{i-1}) =$$

$$\begin{bmatrix} P(t_{i-1}/t_{i-1}) & 0 & 0 \\ 0 & Q(t_{i-1}) & 0 \\ 0 & 0 & R(t_{i-1}) \end{bmatrix} \tag{21}$$

Where the subscript 'a 'denotes augmentation [1]. The dimensions of the augmented state are the sum of the length of the state vectors, process noise vector, and the measurement noise that is

$$L = n_x + w_x + v_x \tag{22}$$

Let $W_m^{(0)}$ be the weight of mean at that point, which is indexed as zeroth point and the associated weight with the generated sigma points is discussed below

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$$W_m^{(0)} = \frac{\lambda}{\lambda+L} \quad (23)$$

$$W_C^{(0)} = \frac{\lambda}{\lambda+L} + (1-\alpha^2+B) \quad (24)$$

$$W_m^{(i)} = W_c^{(i)} = \frac{\lambda}{2(\lambda+L)} \quad (25)$$

Here $\lambda = \alpha^2 (L + k) - L$ and α is the primary scale parameter and it finds outs the spreading of the sigma points around the mean value and its value is normally considered positive. The steady k is the secondary scale parameter and it is worn to approximate the higher-order terms and β denotes the distribution of x.

- **UPDATION OF TIME**

The processing model at each instant point is given by

$$\hat{x}^{(i)} = A(t_{i-1})\, x_x^{(i)} + x_v^{(i)} \quad (26)$$

The predicted mean is

$$\hat{\mu} = \sum_{i=0}^{2L} \hat{x}^{(i)}\, W_m^{(i)} \quad (27)$$

The predicted covariance is

$$P(t_{i-1} / t_{i-1}) = \sum_{i=0}^{2L} W_C^{(i)} \left\{\hat{x}^{(i)} - \hat{\mu}\right\}\left\{\hat{x}^{(i)} - \hat{\mu}\right\}^T + Q(t_{i-1}) \quad (28)$$

- **UPDATE OF MEASUREMENT**

The measurement model at each instant point is given by

$$\hat{z}_n^{(i)} = h_n^a\left(t, \hat{x}^{(i)}\right) + x_V^{(i)} \quad (29)$$

Where n is the nth reader among N (t_i) RFID readers and its values n = 1,2,3………. N (t_i)

The measurement from RSSI at time t_i is given by

$$h_n^a\left(t, \hat{x}^{(i)}\right) = \sqrt{\left(\hat{x}^{(i)} - x_n(0)\right)^2 + \left(\hat{y}^{(i)} - y_n(0)\right)^2} \quad (30)$$

The predicted surveillance is given by

$$\hat{z}_n = \sum_{i=0}^{2L} \hat{z}^{(i)}\, W_m^{(i)} \quad (31)$$

The Innovation covariance is given by

$$S_n(t_{i-1}) = \sum_{i=0}^{2L} W_C^{(i)} \left\{\hat{z}_n^{(i)} - \hat{z}_n\right\}\left\{\hat{z}_n^{(i)} - \hat{z}_n\right\}^T + R_n(t_{i-1}) \quad (32)$$

The cross covariance matrix is given by

$$P_{xz,n}(t_{i-1}) = \sum_{i=0}^{2L} W_C^{(i)} \left\{\hat{z}_n^{(i)} - \hat{z}_n\right\}\left\{\hat{z}_n^{(i)} - \hat{z}_n\right\}^T \quad (33)$$

At last, the updating is done by

$$\hat{x}(t_i / t_i) = \hat{x}(t_i / t_{i-1}) + \sum_{n=1}^{N(t_1)} K_n(t_{i-1})\left\{z_n(t_i) - \hat{z}_n\right\} \quad (34)$$

Where K_n (t_i)is given by

$$K_n(t_i) = P_{xz,n}(t_i) S_n^{-1}(t_i) \quad (35)$$

The estimated covariance is given by

$$P(t_i/t_i) = P(t_i/t_{i-1}) - \sum_{n=1}^{N(t_1)} K_n(t_{i-1})\, R_n(t_{i-1})\, K_n^T(t_{i-1}) \quad (36)$$

3. ACCURACY CHECK

From [18], the test accuracy of this intelligent model is measured by

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \quad (37)$$

III. EXPERIMENTAL RESULTS

This experiment has been done in a sequence of two case studies where tracking of two different random objects has been done. This experiment is performed for the duration of 1 hour on the random data generated in a specific duration of time; it will also categorize the incoming and outgoing movement of the objects.

- **Data Generation**

This Proposed intelligent tracking model is artificially experimented on the software platform by considering the area of 100 x 100 m^2 where 4 UHF RFID readers are placed at the corner of the chosen area. For convenience 28 tags are placed on the floor and then identification, localization, and tracking have experimented. This intelligent surveillance model is implemented on MATLAB 2020, deep learning Residual Network 101 tool. The initial state in the process of tracking of the object in the 2D indoor tracking is x_0 = [x(0) y(0)]. By test and trail, sampling time is T = 0.05s, and initial assumed covariance matrix is P_0 = diag (0.10).

1. Case Study I

In the first case study, localization and tracking of the randomly chosen object were experimented with concerning RFID antenna 1.

Then the number of readings of RSSI values is collected from the RFID antennas when the object 1 is moving. These RSSI values obtained from the RFID antennas are processed to create samples as shown in figure 4.

TABLE-1: Number of RSSI readings at the RFID Antennas

RFID Antenna		Number of readings of RSSI and its corresponding value in dBm									
1	Watt	20	19	24	18	21	25	23	16	17	22
	dBm	-76	-65	-37	-44	-62	-35	-80	-75	-33	-79
2	Watt	17	16	21	15	18	22	20	13	14	19
	dBm	-43	-75	-57	-30	-46	-81	-83	-58	-60	-58
3	Watt	13	12	17	11	14	18	16	9	10	15
	dBm	-72	-58	-41	-64	-57	-80	-35	-74	-64	-49
4	Watt	10	9	14	8	11	15	13	6	7	12
	dBm	-42	-79	-53	-37	-47	-72	-66	-55	-81	-62

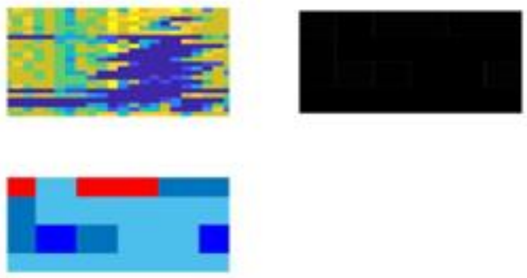

Figure-4: Samples generated in case the study I when Object 1 is moving concerning RFID antenna 1

These samples are given as input to the CNN for further processing and in the identification of the object position. The dimensions of each sample are 224*224*3. These samples are used in the localization of objects in the area of 100*100 m^2 and localization of multi-objects have been experimented as shown in figure 5.

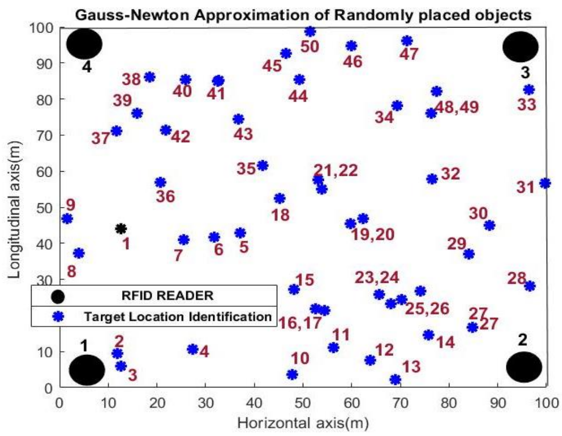

Figure-5: Indoor Localization

In the case study I, object 1 is randomly selected from figure 5 which is denoted by the black (*) sign for tracking, and this tracking of object 1 has been done concerning RFID antenna 1.

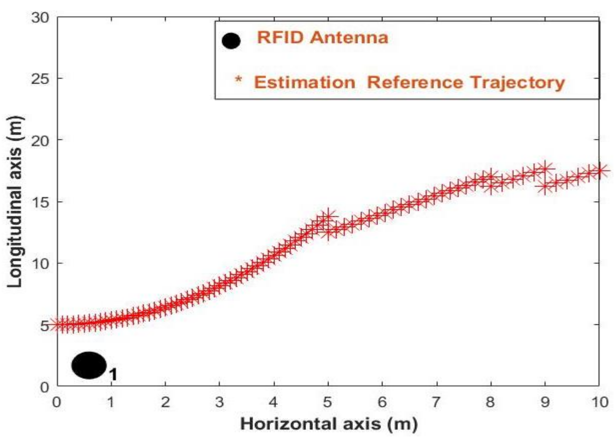

Figure-6: Estimated Reference Trajectory concerning the RFID Antenna 1

For tracking of randomly selected objects from figure 5, the reference trajectory on which the randomly selected object 1 will move is shown in figure 6.

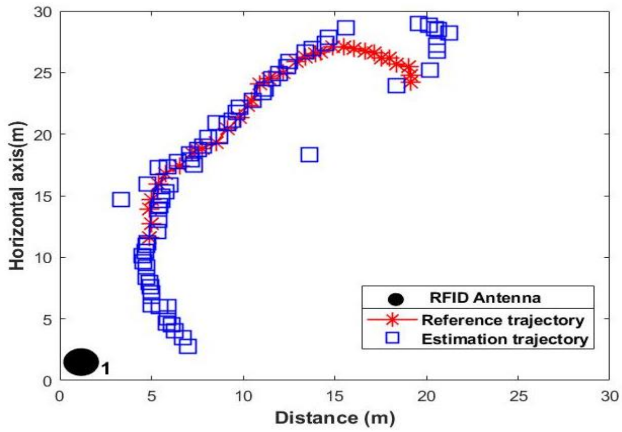

Figure-7:- Estimated trajectory in the horizontal axis concerning the RFID Antenna 1

The estimated horizontal trajectory is shown in figure 7, this figure shows that object 1 is moving on the reference path which is plotted concerning RFID Antenna 1.

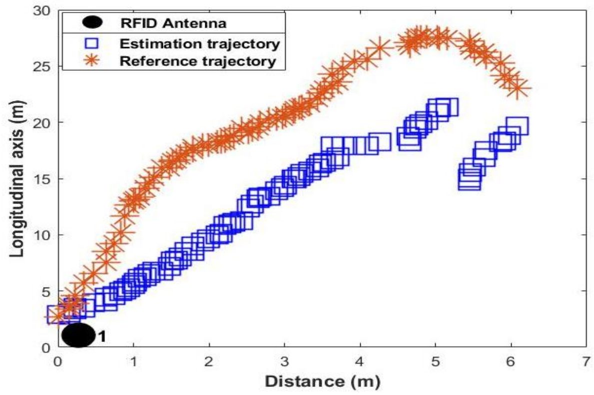

Figure-8: Estimated Trajectory in the longitudinal axis concerning RFID Antenna 1

As shown in figure 8, the estimated longitudinal trajectory of object 1 concerning the RFID antenna 1. The minimum tracking error obtained in the longitudinal and the horizontal trajectory is shown in figure 9.

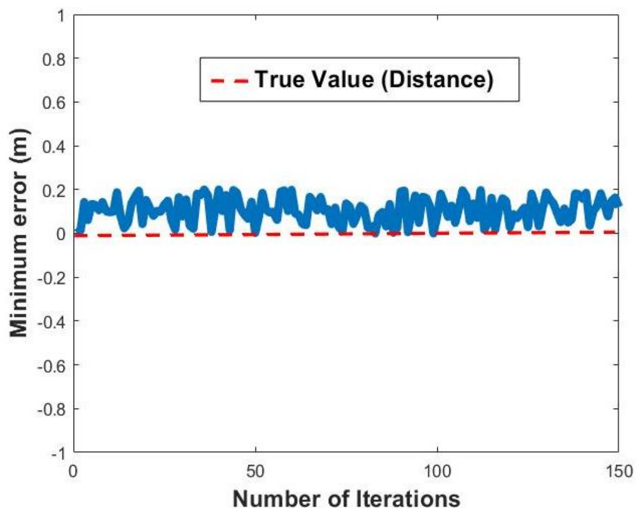

Figure-9: Minimum tracking error Vs number of iterations

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2. Case study II

In the second case study, localization and tracking of the randomly chosen object experimented concerning the RFID antenna 3. The RSSI generated from the RFID readers in case study II is shown in table II.

TABLE-2: Number of RSSI readings at the RFID Antennas

RFID Antenna		Number of readings of RSSI and its corresponding value in dBm									
1	Watt	13	11	9	10	12	8	14	6	7	15
	dBm	-54	-77	-82	-63	-36	-71	-42	-43	-47	-48
2	Watt	16	14	12	13	15	11	17	9	10	18
	dBm	-48	-75	-79	-66	-50	-84	-43	-34	-78	-43
3	Watt	20	18	16	17	19	15	21	13	14	22
	dBm	-74	-52	-67	-50	-62	-55	-50	-41	-80	-41
4	Watt	23	21	19	20	22	18	24	16	17	25
	dBm	-54	-60	-30	-49	-71	-48	-68	-59	-49	-45

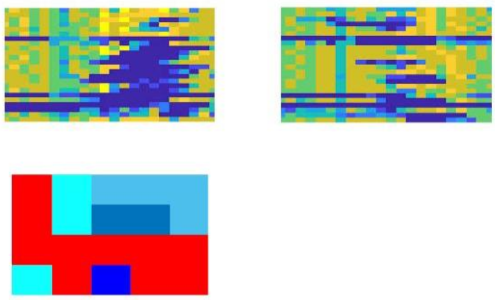

Figure-10: Samples generated in the case study II when Object 2 is moving concerning the RFID antenna 3.

The samples generated from the received RSSI are shown in figure 10 and the dimensions of these samples are 224*224*3. These samples are used in the localization of objects in the indoor scenario as shown in figure 11.

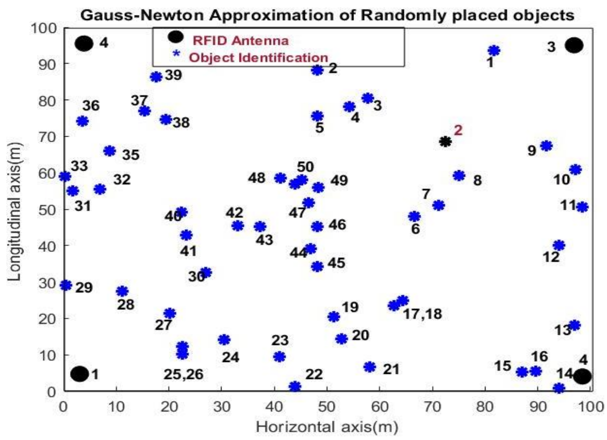

Figure-11: Indoor Localization

In this case study, object 2 is randomly chosen from figure 11 which is nearer to the RFID antenna 3 for tracking. In this case tracking of object 2 which is denoted by the black (*) sign is done concerning the RFID antenna 3 is shown in figure 11.

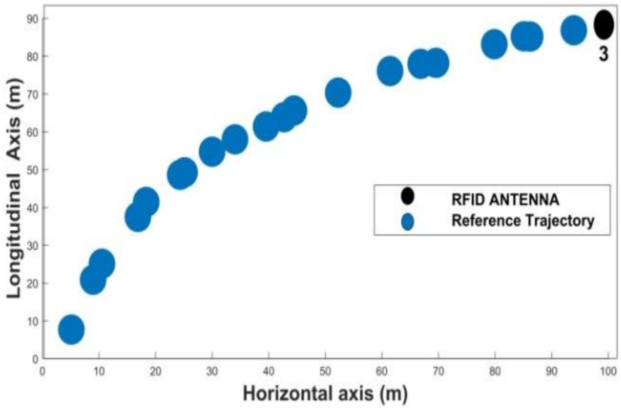

Figure-12: Estimated Reference Trajectory concerning the RFID Antenna 3

The estimated reference trajectory concerning the RFID antenna 3 is shown in figure 12.

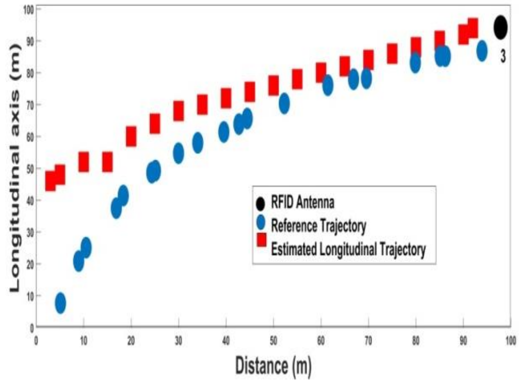

Figure-13: Estimated Longitudinal Trajectory concerning the RFID Antenna 3

The estimated path in the longitudinal trajectory and the horizontal trajectory of randomly chosen object 2 from figure 11 is shown in figure 13 and figure 14 respectively.

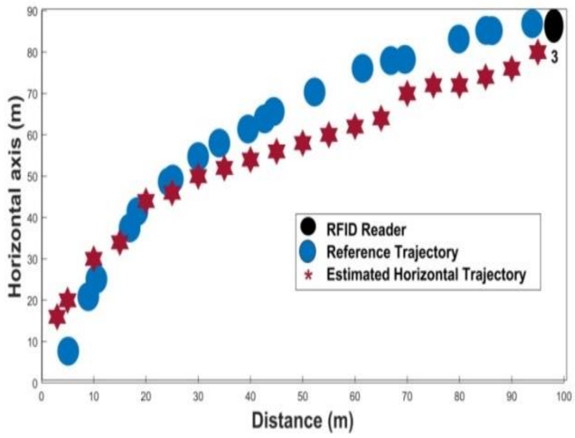

Figure-14: Estimated Horizontal axis Trajectory concerning the RFID antenna 3

The minimum tracking error in the longitudinal and horizontal trajectory in case study II is shown in figure 15.

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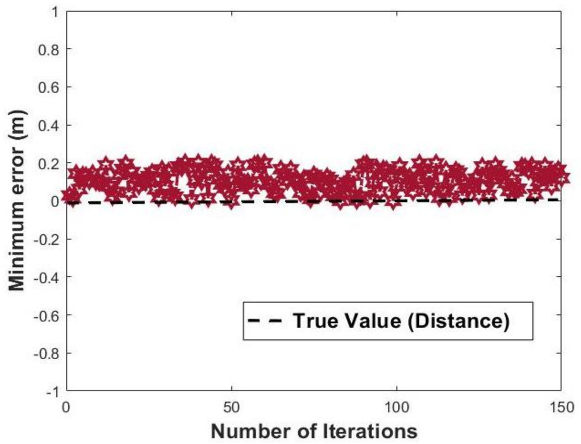

Figure-15: Minimum tracking error Vs numbers of iterations

3. Experimental Values

Table III shows the number of objects IN and OUT and the numbers of moving objects in the two case studies are shown in the table.

Table-3: The Outcome of the Experiment

Case Study	I	II
Total Number of Objects Counts in 1 hour	97	77
Net Distance Travelled By Object	15meters	19 meters
Predicted number of objects IN	45	45
Predicted number of objects OUT	29	30
Predicted number of objects PASS (Moving)	23	2
Accuracy Check	98%	98%

The observed parameters during the experiment of the intelligent tracking model based on RFID localization are shown in table 4

Table-4: Parameters Observed

	Case Study I	Case Study II
Network Size	100*100 m^2	100*100 m^2
P_t(Transmitted Power)	100 Watt(w)	100 Watt(w)
P_L(Power Loss)	30 Watt(w)	30(Watt)w
Noise	0.731	0.4624
mean	0	0
Standard deviation	1	1
Localization error	12.408	13.937
Number iteration	150	150

IV. CONCLUSION

The obtained accuracy is 98 percent which is due to the complex indoor environment and this can be further improved in future work. The experimental outcome shows that this AI-based intelligent surveillance model is successfully implemented and it provides better performance in terms of precision, effectiveness. The proposed application can be adaptively implemented for multi-object localization and multi-tracking trajectories.

REFERENCES

1. Jitendra Damade and Agya Mishra, "Indoor RFID tracking System based on UKF Fusion Estimation Techniques" in CiiT International Journal of Digital Signal Processing, Vol. 9, No 7, August – September 2017 pp.129-134
2. Guillermo Alvarez-Narciandi, Andrea Motroni, Marcos R. Pino, Alice Buffi, Paolo Nepa, "A UHF-RFID gate control system based on a Convolution Neural Network" in 2019 IEEE International Conference on RFID Technology and Applications (RFID-TA), 978-1-7281-0589-5/19/$31.00 ©2019 IEEE, pp 353-356.
3. Iyeyinka Damilola Olayanju, Olabode Paul Ojelab, "Using Multilateration and Extended Kalman Filter for Localization of RFID Passive Tag in NLOS" in Blekinge Institute of Technology February 2010, pp.1-49.
4. M. Truijens, X. Wang, H. de Graaf, and J. J. Liu, "Evaluating the Performance of Absolute RSSI Positioning Algorithm-Based Micro zoning and RFID in Construction Materials Tracking "in Hindawi Publishing Corporation Mathematical Problems in Engineering, Volume 2014, Article ID 784395, 8pages pp.1-8 http://dx.doi.org/10.1155/2014/784395
5. Nasir Kenarangui, "Real-Time Location Tool for Precision Tracking of Passive UHF RFID Tags in Two Dimensions" in the University Of Texas at Arlington August 2010,pp.1-70.
6. ∗Jin Xue-Bo, Nie Chun-Xue, Shi Yan, and Su Ting-Li, "Maneuvering Target Tracking with UKF and EKF for Indoor RFID System" in International Journal of Control and Automation, Vol.9, No.2 (2016),pp.411-424 http://dx.doi.org/10.14257/ijca.2016.9.2.39
7. JIN Xue-bo, SRI Van, Nie Chun-Xue, "Tracking for Indoor RFID System with UKF and EKF" in 2015 International Conference on Estimation, Detection and Information Fusion (ICEDIF 2015), 978-1-4799-6418-5/15/$3\.00 ©20151EEE, pp.146-151.
8. Xue-bo Jin, "UKF Fusion Estimation for Indoor RFID Tracking" in Applied Mechanics and Materials Vols. 427-429 (2013) pp 582-585 Online available since 2013/Sep/27 at www.scientific.net © (2013) Trans Tech Publications, pp. 582-585.Switzerland doi:10.4028/www.scientific.net/AMM.427-429.582
9. S. L. Ting, L. X. Wang, W. H. Ip , "A study of RFID adoption for vehicle tracking in a container terminal" in Journal of Industrial Engineering and Management pp. 22-52 http://dx.doi.org/10.3926/jiem.412
10. Chao Peng, Hong Jiang, and Liangdong Qu, "Deep Convolution Neural Network for passive RFID Tag localization via joint RSSI and PDOA fingerprinting features" in IEEE, Jan 2021, Volume 9, pp.15441-15451
11. Rikiya Yamashita, Mizuho Nishio, Richard kinh Gian Do, Kaori Togashi ,"Convolution neural networks: an overview and application in radiology" in Springer, Insights into imaging,2018, pp.611-629.
12. Zhonghua Li, Guannan He, Muyuan Li, Jinqiu Huang, Jianzhong Cao, Shuo Feng, Le Ma, Qiaofang Chen, Haijian Gao, Shanjin Wang, "RBF Neural Network Based RFID Indoor Localization Method Using Artificial Immune System" in the 30th Chinese Control and Decision Conference (2018 CCDC) pp.2837-2842
13. A. Terejanu, "Unscented Kalman Filter Tutorial" Gabriel Department of Computer Science and Engineering University at Buffalo, Buffalo, NY 14260,pp. 1-6 terejanu@buffalo.edu
14. Abdul Malik Shaaria and Nur Safwati Mohd Norb*, "Position and Orientation Detection of Stored Object Using RFID" in Advances in Material & Processing Technologies Conference, 1877-7058 © 2017 The Authors. Published by Elsevier Ltd, pp.708-715doi: 10.1016/j.proeng.2017.04.146
15. A. Bhatia, B. Mehta, R. Gupta, "Different Localization Techniques for Real-Time Location Sensing using passive RFID", Department of Electrical Engineering, Indian Institute of Technology, Kanpur-208016, India 8/12/2007, pp.1-32.
16. Dirk Hahnel, Wolfram Burgard, Dieter Fox, Ken Fishkin, Matthai Philipos, "Mapping and Localization with RFID Technology".
17. Samer S.Saab, Zahi S. Nakad, "A standalone RFID Indoor Positioning System Using Passive Tags" in IEEE Transactions On In dustrial Electronics, VOL.58,NO.5 , May 2011, pp 1961-1970

18. Noopur Soni, Dr. Agya Mishra, "Intelligent RFID-Based Localization and Tracking Model Design Using Unscented Kalman Filter and Convolution Neural Network" in IEEE conference 4th International Conference On Smart Systems and Incentive Technology for 20th to 22th January 2022 at Francis Xavier Engineering College, Tirunelveli, India, pp. 1128-1134

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