Original scientific paper

https://doi.org/10.33180/InfMIDEM2023.401

Informacije MIDEM
Journal of Microelectronics,
Electronic Components and Materials
Vol. 53, No. 4(2023), 207 – 223

Virtual Reference Tag Assisted Radio Frequency Identification Localization and Tracking Using Artificial Intellect Techniques in Indoor Environment

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Abstract: The application of Radio Frequency Identification (RFID) technology for localizing and tracking mobile objects within indoor environments, primarily relying on Received Signal Strength Indicator (RSSI) readings, poses challenges in enhancing tracking accuracy and minimizing errors. In response, we present the VIRALTRACK (Virtual Reference Tag Localization and Tracking) model, comprising four key processes: signal improvement, optimization-based virtual reference tag allocation, quantum-based localization, and deep reinforcement learning-based tracking. The Extended Gradient Filter (EGF) algorithm is introduced to mitigate RSSI fluctuations, thereby enhancing signal efficiency. The Emperor Penguin Colony (EPC) optimization algorithm allocates virtual reference tags, factoring in Signal-to-Noise Ratio (SNR), tag quantity, and environmental conditions, elevating tracking accuracy. Quantum Neural Network (QNN) facilitates precise position estimation for moving targets, with the SignRank algorithm optimizing virtual reference tag selection to reduce tracking errors. The Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm ensures effective tracking by considering distance, phase, orientation, and previous coordinates. Simulations conducted using the NS3.26 network simulator evaluate performance metrics, including tracking accuracy, tracking error, and cumulative probability, validating the efficacy of the proposed VIRALTRACK model in RFID-based indoor localization and tracking.

Keywords: Radio Frequency Identification (RFID), Virtual Reference Tag Allocation, RFID reader, Quantum Neural Network (QNN), Extended Gradient Filter (EGF)

Radiofrekvenčna identifikacija, lokalizacija in sledenje s pomočjo virtualne referenčne oznake z uporabo tehnik umetne inteligence v notranjem okolju

Izvleček: Uporaba tehnologije radiofrekvenčne identifikacije (RFID) za lociranje in sledenje mobilnih predmetov v notranjih okoljih, ki temelji predvsem na odčitkih indikatorja moči sprejetega signala (RSSI), predstavlja izziv pri izboljšanju natančnosti sledenja in zmanjšanju napak. V odgovor na to predstavljamo model VIRALTRACK (Virtual Reference Tag Localization and Tracking), ki vključuje štiri ključne postopke: izboljšanje signala, dodeljevanje virtualnih referenčnih oznak na podlagi optimizacije, lokalizacijo na podlagi kvantne metode in sledenje na podlagi globokega učenja z okrepitvijo. Uveden je algoritem EGF (Extended Gradient Filter), ki ublaži nihanja RSSI in s tem izboljša učinkovitost signala. Optimizacijski algoritem Emperor Penguin Colony (EPC) dodeljuje virtualne referenčne oznake ob upoštevanju razmerja med signalom in šumom (SNR), količine oznak in okoljskih pogojev, kar povečuje natančnost sledenja. Kvantno nevronsko omrežje (QNN) omogoča natančno ocenjevanje položaja premikajočih se ciljev, algoritem SignRank pa optimizira izbiro navideznih referenčnih oznak, da zmanjša napake pri sledenju. Algoritem TD3 (Twin Delayed Deep Deterministic Policy Gradient) zagotavlja učinkovito sledenje z upoštevanjem razdalje, faze, orientacije in prejšnjih koordinat. Simulacije, izvedene z omrežnim simulatorjem NS3.26, ocenjujejo kazalnike učinkovitosti, vključno z natančnostjo sledenja, napako sledenja in kumulativno verjetnostjo, kar potrjuje učinkovitost predlaganega modela VIRALTRACK pri notranji lokalizaciji in sledenju na podlagi RFID.

Ključne besede: Radiofrekvenčna identifikacija (RFID), dodeljevanje virtualnih referenčnih oznak, bralnik RFID, kvantno nevronsko omrežje (QNN), razširjeni gradientni filter (EGF)

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How to cite:
M. Nagaraj et al., "Virtual Reference Tag Assisted Radio Frequency Identification Localization and Tracking Using Artificial Intellect Techniques in Indoor Environment", Inf. Midem-J. Microelectron. Electron. Compon. Mater., Vol. 53, No. 3(2023), pp. 207–223

1 Introduction

Automatic localization and tracking technologies have garnered significant attention, driven by the increasing prevalence of location-based applications. This is particularly crucial in scenarios such as logistics management and construction worker supervision, where real-time indoor localization and tracking of moving targets play a pivotal role. The conventional Global Positioning System (GPS) faces limitations in indoor tracking due to issues such as signal blocking and non-line-of-sight conditions [1-3]. As a result, Radio Frequency Identification (RFID)-based tracking technology has emerged as a promising solution, showcasing adaptability to large-scale indoor environments and effectiveness in non-line-of-sight conditions [4-5]. In the realm of RFID-based tracking systems, the fundamental components include RFID tags and readers. RFID readers are employed to collect Received Signal Strength Indicator (RSSI) information from moving target tags, fostering communication and enabling the localization and tracking of the target within indoor environments [6-7]. Indoor localization using RFID technology can be categorized into range-free and range-based approaches [8]. The former utilizes connection information like hop size and anchor position, while the latter incorporates distance estimation between the transmitter and receiver for communication [9-10]. Range-based approaches have demonstrated superiority in large-scale scenarios, leveraging precise tag selection based on RSSI [11]. RFID tags are classified into passive, semi-active, and active categories. Passive RFID tags derive power from the electromagnetic field and lack an internal power supply, whereas semi-active tags receive power for internal circuits and broadcasting from the reader's electromagnetic field. Active RFID tags have their power supply for both internal circuits and broadcasting, offering long-range communication and superior tracking accuracy [15-16]. Despite advancements, existing tracking algorithms, such as the Hidden Markov Model (HMM) and linear regression-based approaches, exhibit high tracking errors in indoor environments [17-18]. This motivates the need for further research to enhance tracking accuracy and reduce localization errors in RFID-based indoor tracking systems. The proposed research aims to address these challenges through a multi-faceted approach. Four key processes are formulated to achieve the overarching objective of improved tracking accuracy:

1. Signal Improvement: Mitigating RSSI signal fluctuations arising from multipath effects and interference in indoor environments.
2. Optimization-based Virtual Reference Tag Allocation: Strategically allocating virtual reference tags to optimize tracking accuracy.
3. Quantum-Based Localization: Leveraging quantum-based techniques to enhance the precision of initial target tag localization.
4. Deep Reinforcement Learning-Based Tracking: Employing deep reinforcement learning for dynamic tracking in real-time indoor environments.

Existing RFID-based tracking systems grapple with issues such as interference, signal-blocking, and low positioning accuracy. The proposed research aims to contribute to the refinement of indoor tracking systems, addressing these challenges and enhancing tracking accuracy. The subsequent sections delve into each formulated process, discussing methodologies, challenges, and potential contributions to the field. Fig. 1 represents the general RFID tracking system.

Table 1 represents the notation and description used in our proposed VIRALTRACK model.

Table 1: Notation and its description

Notation	Description
TX_p	The transmission power of the source device
RX_p	The remaining power of the wave at the receiver
RX_g	value of receiver gain
TX_g	transmitter gain
λ	wavelength
d	distance between the source and the destination
V_t	Virtual reference tag
R_t	Reference tag
r^2	Distance from the reference tag in the grid
S_{V_t}	The signal intensity of the virtual reference tag
S_{R_t}	The initial signal intensity of the reference tag
y	Distance factor
ρ	Humidity
K	Temperature
W_{V_t}	Weight value between the input layer and hidden layer
μ_t	The threshold value of $t\,th$ hidden neuron
μ_t	sigmoid function
$\gimel$	Discount factor
TRP	True positive rate
$\mathfrak{Q}$	Number of identified virtual reference tag
ʆ	The total number of virtual reference tags.

This paper introduces the VIRALTRACK model, a novel RFID localization and tracking system designed for indoor environments, incorporating advanced artificial

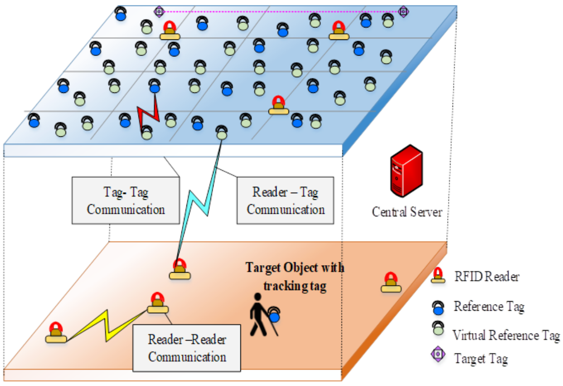

Figure 1: RFID tracking system

intelligence techniques. The key contributions of this research encompass several innovative components. Firstly, the Extended Gradient Filter (EGF) is proposed to effectively mitigate the impact of noise-induced RSSI fluctuations. Secondly, an optimization-based strategy for virtual reference tag allocation is introduced, utilizing the Emperor Penguin Colony (EPC) algorithm. This approach optimizes the number of virtual tags by considering factors such as Signal-to-Noise Ratio (SNR), tag quantity, and environmental conditions like temperature and humidity, ultimately enhancing tracking accuracy. The third contribution involves Quantum-based localization, where the position estimation is achieved through a Quantum-Inspired Neural Network (QNN). The SignRank algorithm is proposed to select the optimal virtual reference tag within specific grids, aiming to reduce errors during tracking. Lastly, deep reinforcement learning-based tracking is presented, employing the Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm. This method takes into account various parameters, including distance, phase, orientation, and previous coordinates, leading to a substantial improvement in tracking accuracy within indoor environments. The proposed VIRALTRACK method is thoroughly evaluated based on tracking accuracy, tracking error, and cumulative probability, demonstrating its effectiveness in addressing challenges associated with RFID localization and tracking in indoor settings.

2 Literature survey

In the realm of indoor object tracking for e-health applications, Radio Frequency Identification (RFID) technology has emerged as a prominent solution, as evidenced by various proposals in the literature. One such proposition by Author [21] advocates for the use of ultra-high frequency RFID to facilitate tracking and management of mobile tags within indoor environments, particularly emphasizing its application in hospitals. This system relies on signal information exchanged between RFID readers and tags, with a focus on utilizing received signal strength for precise localization of patients and medical items. Meanwhile, Author [22] proposes an indoor tracking system that integrates RFID information with Inertial Measurement Unit (IMU) data. Although the system employs the unscented Kalman filter algorithm based on Received Signal Strength Indication (RSSI) data, its limitations in non-Gaussian environments are acknowledged.

In an attempt to address challenges associated with RFID-based tracking, innovative methods are explored. Author [23] introduces a spinning antenna-based system, employing three key pieces of information—RSSI, Doppler frequency, and phase—for localization. Notably, preprocessing steps are incorporated to eliminate signal noise, enhancing the accuracy of object localization. On a different front, the work of Author [24] focuses on medical equipment tracking within indoor spaces, utilizing RFID tag information to ascertain the location of each piece of equipment. Moreover, efforts have been made to enhance indoor positioning algorithms, as seen in Author [25]'s work, which incorporates the LANDMARK algorithm and K-Nearest Neighbor (K-NN) algorithm for RFID tags. However, challenges are noted in the initial parameter selection for K-NN, which impacts the system's effectiveness in indoor positioning scenarios.

Various strategies are proposed to compensate for signal loss and improve accuracy in RFID-based tracking. Author [26] introduces a compensating signal loss-based RFID system, leveraging a filter to mitigate ambiguity in gathered information and employing a triangulation algorithm for object localization. Similarly, Author [27] integrates robust support vector regression and Kalman filter algorithms in a reference tag-supported RFID system to track moving objects, with the Kalman filter serving to eliminate RSSI fluctuations from the received signal. Despite the effectiveness of the system, concerns are raised about the time consumption of the support vector regression algorithm, impacting overall tracking accuracy. In the pursuit of efficient tracking in indoor environments, Author [28] presents a model with noise-filtering mechanisms for mobile targets. The system's design includes pre-filter and post-filter components in RFID tags to enhance the tracking process. Moreover, real-time tracking solutions utilizing passive RFID tags and low-frequency transmission are explored by Author [29], underscoring the practical deployment of four passive RFID tags on each moving object for accurate tracking within indoor environments.

The advancement of localization methods extends to the use of complex algorithms such as the particle filter, laser ranging model, and Density-Based Spatial Clustering of Application with Noise (DBSCAN) algorithm, as proposed by Author [30]. The intricacies of tracking are further addressed by Author [31], who introduces an active RFID-based moving target prediction system. This system utilizes virtual reference tags and a linear regression model to effectively track moving objects within indoor locations. Meanwhile, the paradigm shifts in tracking strategies with device-free systems, as illustrated by Author [32], who employs the Hidden Markov Model (HMM) algorithm for trajectory estimation of moving objects. Furthermore, the paper by Author [33] introduces a differential received signal strength-based tracking system for construction equipment within indoor environments, utilizing four RFID readers and signal information from mobile target tags at different positions for precise tracking. A range-free indoor tracking algorithm is also proposed by Author [34], leveraging methods such as Framed Slotted Aloha and Tree Walking algorithms. However, concerns arise regarding the lack of noise removal in this approach, potentially affecting the accuracy of mobile object tracking. Finally, Author [35] proposes an indoor mobile target tracking solution using the multi-direction weight position Kalman filter, which integrates Gaussian weight computation and velocity estimation to remove RSSI fluctuations and noise interference, thereby enhancing overall tracking accuracy in indoor environments. These diverse approaches collectively contribute to the evolving landscape of RFID-based indoor tracking systems, each addressing specific challenges and pushing the boundaries of accuracy and efficiency in different applications.

3 Problem statement

In the realm of RFID indoor tracking, researchers grapple with persistent challenges in enhancing tracking accuracy and minimizing errors. The proposed tracking model, denoted as T_m, introduces a comprehensive approach where 'm' signifies the moving object, and 'P' designates the indoor position based on an RFID reader's specific location [36]. Existing studies reveal several issues; for instance, an optimization algorithm for unconstrained indoor tracking struggles with efficacy in the face of increased RFID tag interference. This algorithm relies solely on the distance parameter, neglecting crucial phase, location, and orientation information, thus diminishing tracking accuracy [36].

$$T_m = \{ \left(m\left(P_1, P_2, \ldots, P_n\right)\right) | \left(\forall P_n\right)\left(P_n \in L_m \cdot \left(P_n.t < P_{n+1}.t_m\right)\right) \}$$

Another set of challenges arises in a semi-active RFID system that encounters difficulties due to inadequate noise removal and the dependence on triggers for signal transmission [37]. Additionally, the limitation of a single RFID reader poses challenges in effectively tracking multiple mobile targets [37]. These issues persist in data-driven approaches, like the KNN-HMM algorithm, which grapples with complexities in initial parameter selection and time consumption, ultimately diminishing tracking accuracy [38]. Similarly, passive RFID-based real-time tracking systems face particle filter-related challenges, including particle degradation and sample depletion, particularly in non-Gaussian environments [39]. Moreover, the utilization of passive RFID tags introduces constraints related to power resources and real-time tracking feasibility [39].

In a distinct approach, an indoor positioning system relying on the support vector regression algorithm contends with challenges stemming from ineffective noise removal mechanisms, reduced localization accuracy due to excessive reference tags, and prolonged processing times [40]. These collective challenges underscore the need for innovative solutions to enhance the robustness and precision of RFID-based indoor tracking systems [40].

4 Viraltrack system model

In our proposed work, we confront the pervasive challenges inherent in existing indoor mobile object tracking systems. The architecture of our devised system encompasses five pivotal components: RFID readers, real reference tags, virtual reference tags, target tags, and a centralized server. Opting for active RFID tags, we leverage their extended communication range and independence from power sources, drawing an advantage for enhanced performance. Our conceptualization adopts a 3D grid configuration, recognizing the efficacy of real-time indoor tracking within a three-dimensional spatial context. To strategically deploy our system, we position four RFID readers in the ceiling of the indoor environment, complemented by a singular real reference tag allocated to each grid. Our primary objective revolves around augmenting tracking accuracy and curbing localization errors within the indoor setting. The procedural framework of the proposed VIRALTRACK system is illustrated in Fig. 2.

The first critical process in our framework is signal improvement, where we introduce the Extended Gradient Filter (EGF) algorithm. This algorithm operates by effectively minimizing fluctuations in Received Signal Strength Indicator (RSSI), thereby enhancing signal stability and, consequently, improving tracking accuracy. The second process revolves around optimization-based virtual reference tag allocation. Here, we employ the Emperor Penguin Colony (EPC) optimization algorithm to strategically assign virtual reference tags, addressing interference issues associated with real reference tags in the RFID tracking system. By optimizing the allocation of virtual reference tags, we elevate tracking accuracy.

The third pivotal process introduces quantum-based localization, incorporating the Quantum Neural Network (QNN). This quantum-inspired approach accelerates initial position estimation, leading to optimal results in moving object localization. By leveraging quantum principles, we navigate challenges associated with conventional methods, reducing errors during the tracking process. The final process employs deep reinforcement learning-based tracking, employing the Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm. This algorithm harnesses RFID reader information to accurately track moving target tags, contributing to a comprehensive solution for increased tracking accuracy within the indoor environment.

In summary, our VIRALTRACK model integrates these four processes cohesively, culminating in a robust system that adeptly addresses the intricacies of indoor mobile object tracking, demonstrating enhanced tracking precision and reduced localization inaccuracies.

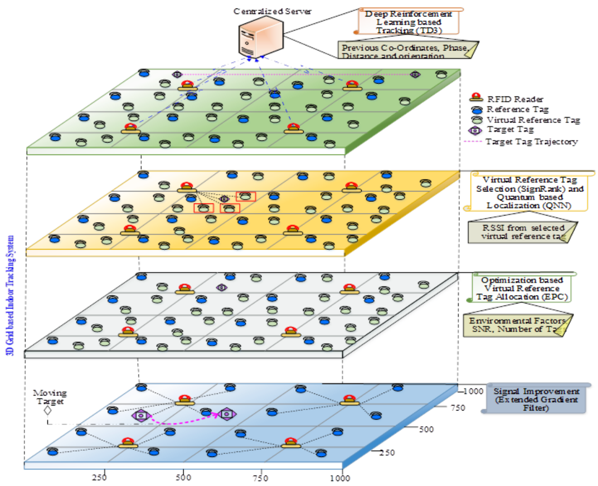

Figure 2: Proposed VIRALTRACK System model

4.1 Signal improvement

The primary process in our work is a signal improvement since the indoor environment is highly affected by the multipath effects, dead spots and interference. These issues increase the noises in the received RSSI signal. RSSI is a good indicator to predict the unknown node's current position. RSSI is an estimation of dBm, which is 10 times the logarithm of the power ratio p at the receiving end and the reference power p_r. This value is inversely proportional to the square of the distance. Hence, our work employs the EGF algorithm to effectively remove the RSSI fluctuations caused by the noise. The reason for selecting this algorithm is that it performs better in multipath conditions. Besides, it performs better than traditional algorithms such as the Kalman filter.

In addition to RSSI, we evaluate the link quality evaluator (LQI) that measures the position by beacon message transmission. The low and high-frequency ranges of RSSI and LQI can be followed: -75dBm and -25dBm for low RF and high RF and 105 for low RF, and 108 for high RF, respectively. A good measurement or estimation of RSSI is required to understand the target positions. When the distance increases, then the RSS value get decreases, and it's formulated as follows:

$$RSSI = -\left(10 n log 10 d + A\right) \tag{1}$$

Where n represents the constant variable for signal propagation, also called

To measure the distance between the reference tags to the RFID readers, the following distance is computed as follows,

$$Distance = \frac{\left(RSSI - A\right) / \left(10 - 10n\right) - 1}{S} \tag{2}$$

Then, measures the signal attenuation factor by the following equation,

$$N = \frac{RSSI - A}{-10 \log 10\left(sd + 1\right)} \tag{3}$$

The computation of RSS is that transmission power is configured in the transmitting device *TX* and receiving distance *RX* with power. Based on the Friis Free Space Transmission Model, the RSS value decreases as the distance of the source device, which is formulated as follows,

$$RX_p = TX_p \times TX_g \times RX_g \left(\frac{\lambda}{4\pi d}\right)^2 \tag{4}$$

Where TX_p is the transmission power of the source device, RX_p is the remaining power of the wave at the receiver, RX_g is the value of receiver gain, TX_g Is the transmitter gain, λ is the wavelength, and d represents the distance between the source and the destination. Then, the RSS value is transformed into the RSSI, which describes the received power of the reference power. P_r and the absolute value of P_r Is 1? mW. The RSSI value is computed as follows,

$$RSSI = 10 * log \frac{RX_p}{RF_p} [RSSI] = dB \quad (5)$$

However, the increased received power result shows a higher value of RSSI and the relationship between the RSSI and received signal power is measured, and the distance *d* is inversely proportional to the RSSI and the ideal distribution of RX_d Is not applicable. Further, the radio signal's propagation is interfered with many influencing effects. A set of RSSI values computes a mean value of RSSI, and the few packets are required from each reference tag and RSSI over the time series is computed as follows,

$$\overline{RSSI} = \frac{1}{n} \sum_{i=0}^{i=n} RSSI_i \quad (6)$$

If the EKF is applied on the RSSI signals, the approximation is applied, i.e. $a = 0.75$ and the approach uses the large difference in RSSI values normalized. It is formulated as follows,

$$RSSIn = a \times RSSIn + (1-a) * RSSIn - 1 \quad (7)$$

The above equation means that the RSSI value corresponding to the signal strength over the distance is based on the past mean value and the currently obtained value of RSSI. Approximation technique is applied to EKF for signal quality enhancement which ranges between 0 and 1, and if the value is 0, then signal quality filtering is no performed. Otherwise, it's executed optimally. In the following, we described the filtering of RSSI signals based on the obtained values of LQI and RSSI.

The following equation performs the value of LQI-based signal smoothing,

$$normalize_{RSSI_{(LQI(t))}} = a \times RSSI_t + (1-a) \times RSSI_{t-1} \quad (8)$$

The fusion value of LQI and RSSI by the normalized RSSI can be as follows,

$$normalize_{RSSI_{(Fusion(t))}} = a \times RSSI_t + (1-a) \times RSSI_{t-1} \quad (9)$$

Finally, the proposed normalization is executed by RSSIs and LQI values of recently measured are computed, and it's executed by the following,

$$normalize_{RSSI_{(Both(t))}} = a \times RSSI_t + (1-a) \times RSSI_{t-1} \quad (10)$$

Therefore, EGF is applied by normalization of LQI and RSSI values, and it is performed in Fig. 3

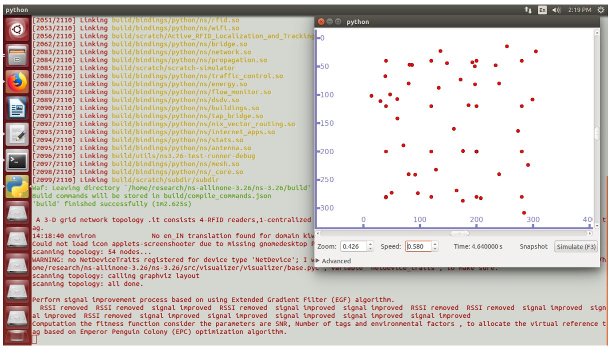

Figure 3: Conditions for Signal Quality Improvement

4.2 Optimization-based virtual reference tag allocation

Our work deploys virtual reference tags in indoor tracking to overwhelm the issues of real reference tags in the RFID tracking system. In our 3D grid network, we place one real reference tag in each grid. To reduce the interference created by the real reference tag. This is achieved by reducing the number of real reference tags via virtual reference tags. Here, the virtual reference tags are allocated by the RFID reader node placed on the ceiling of the indoor environment. It allocates several virtual reference tags by exploiting the Emperor Penguin Colony (EPC) optimization algorithm. It performs faster than traditional optimization algorithms (GWO, PSO, ACO) by obtaining results within the four iterations. It considers the succeeding parameters to compute the fitness function: SNR, number of tags and environmental factors such as temperature and humidity; these parameters are collectively termed attributes. Since these two environmental factors affect the RSSI signal in the indoor environment, based on this information, the RFID reader allocates virtual reference tags for each grid it monitors. In EPC, the optimization is based on the heat transfer and attractiveness between the penguins. Similarly, the virtual reference tags are allocated based on the attributes in our process. Initially, the position of the virtual reference tag is plotted based on the distance from the reference tag, which can be formulated as,

$$V_t = \frac{R_t}{r^2} (11)$$

Where V_t denotes the virtual reference tag, R_t denotes the reference tag and r^2 denotes the distance from the reference tag in the grid. The interference is also considered and minimized to facilitate effective communication between the tags, which can be formulated as,

$$S_{V_t} = S_{R_t} e^{-\lambda y} \quad (12)$$

Where S_{V_t} denotes the signal intensity of the virtual reference tag, S_{R_t} Denotes the initial signal intensity of the reference tag, λ denotes the signal coefficient, and y denotes the distance factor, respectively. From this, the attractiveness G can be formulated as,

$$G = A\delta\rho K_s^4 e^{-\lambda y} \tag{13}$$

Where A denotes the surface area of the grid, δ denotes the connectivity factor, ρ denotes the humidity, and K denotes the temperature, which affects the received signals strength. The orientation of the spiral movement of the penguin is represented as,

$$\text{X axis}= \eta\cos\theta e^{\mu\theta} \tag{14}$$

$$\text{Y axis}= \eta\sin\theta e^{\mu\theta} \tag{15}$$

1. **Pseudo code: EPC algorithm**

Initialization of population of tags;
Compute tag position;
Compute signal strength (S) function;
Determine reference tag position;
For *iter* = 1 to Max_{iter} do
  Compute repeat copies of tag population;
  For i=1 to k population, do
   For j=1 to k population, do
    If $S_j < S_i$ then
     Compute interference using eqn (12)
     Compute attractiveness using eqn (17)
     Compute spiral movement using eqn (14,15)
     Compute updation of position using eqn (19)
    End
   End
  End
Perform sorting and determine the best solution;
Update mutation factor;
Update signal coefficient;
end

The two points separated by a distance in the search space are calculated, which is represented as,

$$D = \int_{\theta_i}^{\theta_j} \sqrt{\eta^2\mu^2 e^{2\mu\theta} + \eta^2 e^{2\mu\theta}}\, d\theta \tag{16}$$

The multiplication of distance and attractiveness is performed to optimally allocate the position of the virtual reference tag, which can be expressed as,

The new position of the penguin is computed by adding the current position with the product of a random vector and mutation factor, which can be formulated as,

$$U_p = \left(x_P, y_P\right) + \alpha\gamma \tag{19}$$

Where α, γ denote the mutation factor and random vector, respectively. This way of allocating the virtual reference tag increases the tracking accuracy and reduces the error involved in tracking the target tag. The pseudo-code of the proposed virtual reference tag allocation is presented below.

4.3 Quantum based localization

To track the target moving tag, our work estimates its position by a localization process. For this, we execute **Quantum inspired Neural Network (QNN)** to estimate the exact position of the moving target. To find the initial position of the target tag, the RFID reader considers the RSSI signal from the nearest virtual reference tag. QNN algorithm includes quantum computation and neural networks, improving the neural network's efficiency. QNN executes based on the quantum neuron model, representing the transition relationship between the quantum states and neuron states derived from logic gates. This algorithm includes three layers input layer, hidden layer and output layer. Here RFID reader considers the RSSI signal for detecting the initial position of the target tag. RSSI signal information is considered as input, and the inputs are converted into a range value of quantum state [0,1] with range $\left[0, \frac{\pi}{2}\right]$ and the calculation of the input layer is defined as follows,

$$X_n^s = F\left(Z_n^s\right) \tag{20}$$

$$Z_n^s = \frac{\pi}{2}.Y_n \tag{21}$$

Where n represent the number of neurons and Y_n It is the nth input variable of the network, and the value of

$$x_P = \eta e^{\mu\frac{1}{\mu}ln\left\{(1-G)e^{\mu\tan^{-1}\frac{y_i}{x_i}} + G\,e^{\mu\tan^{-1}\frac{y_j}{x_j}}\right\}} \cos\left\{\frac{1}{\mu}\ln\left\{\left(1-G\right)e^{\mu\tan^{-1}\frac{y_i}{x_i}} + Ge^{\mu\tan^{-1}\frac{y_j}{x_j}}\right\}\right\} \tag{17}$$

$$y_P = \eta e^{\mu\frac{1}{\mu}ln\left\{(1-G)e^{\mu\tan^{-1}\frac{y_i}{x_i}} + G\,e^{\mu\tan^{-1}\frac{y_j}{x_j}}\right\}} \sin\left\{\frac{1}{\mu}\ln\left\{\left(1-G\right)e^{\mu\tan^{-1}\frac{y_i}{x_i}} + Ge^{\mu\tan^{-1}\frac{y_j}{x_j}}\right\}\right\} \tag{18}$$

$n = 1$. X_n^s Represent the input of Quantum. The second layer is a hidden layer that represents the relationship between input and output that is defined as follows,

$$X_t^h = F\left(Z_t^h\right) \tag{22}$$

$$Z_t^h = \frac{\pi}{2}.G\left(\alpha_t\right) - Arg\left(u_t^h\right) \tag{23}$$

$$u_t^h = \sum_{n=1}^{s} w_{tn}.F\left(Z_n^s\right) - F\left(\mu_t\right) = \sum_{n=1}^{s} w_{tn}.e^{i(Z_n^s)} - F(\mu_t) \tag{24}$$

$$= \sum_{n}^{s} w_{tn}.(\cos\left(Z_n^s\right) + isin\left(Z_n^s\right)) - \cos\left(\mu_t\right) - isin\left(\mu_t\right) \tag{25}$$

Where, w_{tn} Represent the weight value between the input layer and hidden layer and μ_t Represent the threshold value of t *th* hidden neuron. Substitute eqn (23) into eqn (25) and obtain z_t^h as defined as follows,

$$z_t^h = \frac{\pi}{2}.G\left(\alpha_t\right) - Arg\left(u_t^h\right) = \frac{\pi}{2}.G\left(\alpha_t\right) \tag{26}$$

$$-Arctan\left(\frac{\sum_{n=1}^{s} w_{tn}.\sin\left(Z_{n-\sin}^s\left(\mu_t\right)\right)}{\sum_{n=1}^{s} w_{tn}.\cos\left(Z_{n-\cos}^s\left(\mu_t\right)\right)}\right)$$

Where each metric belongs to the t[th] neuron in the hidden layer and the value of t=1 and μ_t Represent the sigmoid function.

The output layer provides the output for position prediction that is defined as follows,

$$Z_n = \left|Im\left(x^0\right)\right|^2 \tag{27}$$

$$x^0 = F\left(z^0\right) \tag{28}$$

$$z^0 = \frac{\pi}{2}.G\left(\alpha^0\right) - Arg\left(u^0\right) \tag{29}$$

$$u^0 = \sum_{t=1}^{T} w_t.F\left(z_t^h\right) - F\left(\mu^0\right) = \sum_{t=1}^{T} w_t.ee^{i(Z_n^s)} - F\left(\mu^0\right)(30) \tag{30}$$

$$= \sum_{m}^{M} w_t.\left(\cos\left(z_t^h\right) + isin\left(z_t^h\right)\right) - \cos\left(\mu^0\right) - isin\left(\mu^0\right) \tag{31}$$

Where, w_t Represent the weight value and μ^0 is represent the threshold value of the output neuron. Then substitute the eqn (30) into eqn (31) and obtain (μ^0) as follows,

$$z^0 = \frac{\pi}{2}.G\left(\alpha^0\right) - \arg\left(u^0\right) = \frac{\pi}{2}.G\left(\alpha^0\right) \tag{32}$$

$$-Arctan\left(\frac{\sum_{n=1}^{N} w_t.\sin\left(z_t^h\right) - \sin\left(\mu^0\right)}{\sum_{n=1}^{N} w_t.\cos\left(z_t^h\right) - \cos\left(\mu^0\right)}\right)$$

Where, z^0 represent the output which is known as the optimal position for localization. To select the optimal virtual reference tag for localization, we proposed the **SignRank** algorithm. It ranks the virtual reference tag inside each grid based on its distance. The SignRank algorithm considered the weighted graph from the QINN, and it is defined as follows,

$$G = \left(V, B^+, B^-\right) \tag{33}$$

Where the value of $B_{ij}^+ \, and B_{ij}^-$ are defined as follows,

$$B_{ij}^+ = \begin{cases} 1, & positive\,link\,between\,i\,to\,j \\ 0, & No\,positive\,link\,between\,i\,to\,j \end{cases} \tag{34}$$

$$B_{ij}^- = \begin{cases} 1, & negative\,link\,between\,i\,to\,j \\ 0, & No\,negative\,link\,between\,i\,to\,j \end{cases} \tag{35}$$

This algorithm supposes an RFID reader randomly visits the virtual references tag for localization. The RFID reader visits one neighbour's virtual reference tag, then RFID has positive and negative sign values and the high positive value is denoted as rank one; based on these rank values, the virtual reference tag is selected for localization. This value is based on the distance of the virtual reference tag.

The positive and negative value is updated every time to select the optimal virtual tag. From the ranking, it selects the optimal virtual reference tag for localization. Based on the selected RSSI signal received from the virtual reference tag and moving target tag, the RFID reader localizes the initial position of the moving target tag. This way of localizing the moving target position reduces the error during the tracking.

$$\pi^{+(a+1)} = \beta\left(\sum_{j\in IM_j^+}\pi_j^{+(a)}Q_{ij} + (1-\sigma)\sum_{\in IM_j^-}\pi_j^{-(a)}Q_{ij} + \frac{\sigma}{2M}\sum\nolimits_{j=1}^{M}\pi_j^{-(a)}\right) + \frac{1-\beta}{2M} \tag{36}$$

$$\pi^{-(a+1)} = \beta\left(\sum_{j\in IM_j^-}\pi_j^{+(a)}Q_{ij} + (1-\sigma)\sum_{\in IM_j^+}\pi_j^{-(a)}Q_{ij} + \frac{\sigma}{2M}\sum\nolimits_{j=1}^{M}\pi_j^{-(a)}\right) + \frac{1-\beta}{2M} \tag{37}$$

2. Pseudo code: Quantum-based localization

INPUT: No. of virtual reference tags {*vt*1, *vt*2, ..*vtn*}, d
OUTPUT: Optimal virtual reference tag
Begin
Initialize {*vt*1, *vt*2, ..*vtn*}, RSSI signal
{
For each virtual reference tag {*vt*} do
Calculate weight value for every {*vt*}
End for
}
Optimal position is detected for localization
Take weighted graph (G) from QINN
For every node i in G do
For every neighbor j of node i do
if (Bij+ == 1) then
Select high positive rank node and set high rank using eqn(34)
Optimal virtual reference tag is selected for localization
else if (Bij- == 1) then
Put a low rank for virtual reference tag using eqn(35)
End If
End For
End For

4.4 Deep reinforcement learning based tracking

To track the moving target in the indoor environment, we propose the Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm, one of the deep reinforcement learning algorithms. It is executed by the centralized server using the information acquired by each reader positioned in the indoor environment. It provides better results in tracking by learning the indoor environment effectually. Besides, it outperforms existing reinforcement learning algorithms. It utilizes subsequent parameters to track the moving target: distance, phase, orientation and previous coordinates. By utilizing this information in tracking, our proposed method tracks the moving target tag effectually. The tracking of moving tags is modelled as a Markov Decision Process (MDP), which comprises attributes, namely state (*S*), action (Å), reward (ℝ) and discount factor (ג). The state represents the state space of the system at a time (τ) upon which an action is performed by the agent. Depending on the action, the system receives a reward for each time step. The discount factor denotes the acceptance of current rewards over upcoming ones. The pol-

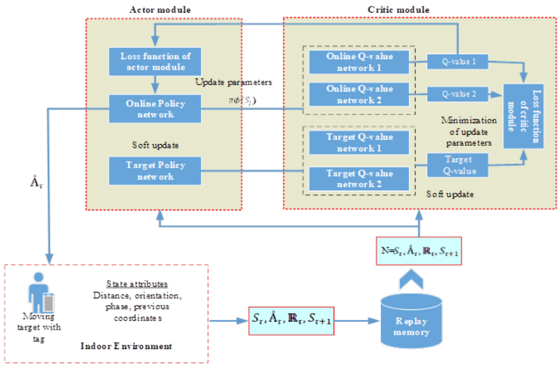

Figure 4a: Process of deep reinforcement learning-based tracking

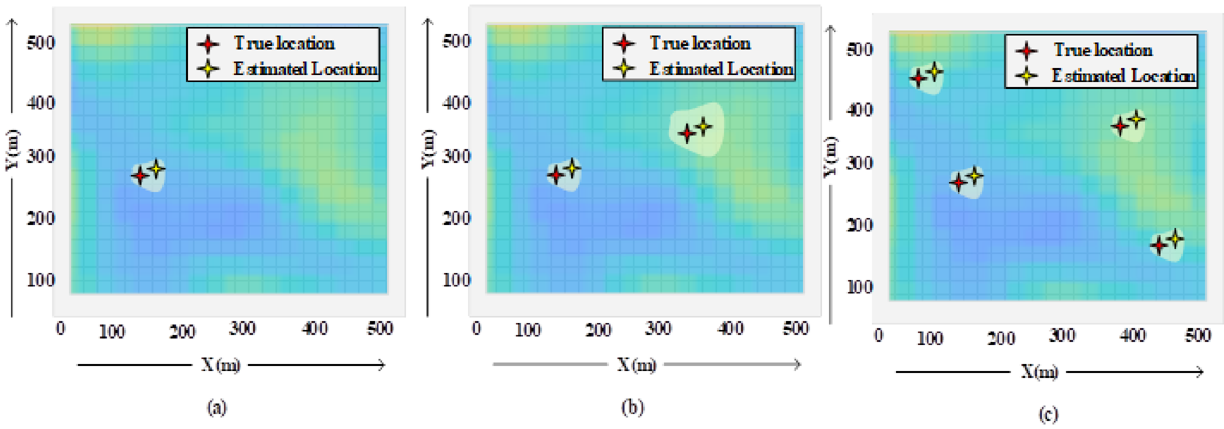

Figure 4b: a) One target b) Two target c) Multi target

icy refers to the selection of action by the agent, and an optimal policy is termed the policy of the agent, which achieves expected returns. In our tracking process, the state is defined as the current position of the moving target tag, which includes the attributes. The process of deep reinforcement learning-based tracking is represented in Fig. 4a, and Fig 4b represents the tracking position of the moving object, 4b.a represent one moving target, 4b.b represent two targets and 4b.c represent multi-target.

The action carried out by the DRL agent is tracking the location based on state attributes. The reward is generated based on how well the agent tracks the target tag. The implementation of tracking is formulated as,

$$Q\left(S,\text{Å}\right)=E_{\pi(s)}[\mathbb{R}_{\tau+1}+ \\ +\lambda Q\left(S_{\tau+1},\text{Å}_{\tau+1}\right)\mid S_{\tau}=S,\text{Å}_{\tau}=\text{Å} \quad (38)$$

The value function on following the policy π (s) is termed as the expected return, which can be formulated as,

$$V_{\pi}\left(s\right)=\sum_{a\in\text{Å}}\pi(|\text{Å}\,S)Q_{\pi}\left(S,\text{Å}\right) \quad (39)$$

The actor module performs actions based on the current state attributes. The actor module is trained accordingly to achieve the optimal policy. The loss obtained in the actor module is formulated as,

$$l_A=E[Q_{\theta 1}\left(S,\text{Å}\right)|_{S=S_j\text{Å},=\pi\phi\left(S_j\right)}] \quad (40)$$

Where ϕ and Θ1 represent the parameters of the online poly network and online Q value network, the critic module is incorporated to evaluate the actions taken by the actor module to achieve the optimal policy. The critic produces the Q value, which is improved by updating the network parameters. The optimal Q-value function is represented as,

$$x_j=\mathbb{R}\left(S_j,\text{Å}_j\right)+\lambda min_{i=1,2}Q_{\hat{\theta}i}\left(S_{j+1},\pi\phi'\left(S_{j+1}\right)\right) \quad (41)$$

Where, $\hat{\theta}i$ and ϕ' Denotes the network parameters of the target Q-value network and target policy network. The reward that the agent can receive by taking an action Å_j in the state S_j is denoted as $\mathbb{R}(S_j, \text{Å}_j)$. The loss function of the critic module can be formulated as,

$$l_C=\frac{1}{N}\sum_{j=1,2}^{N}\sum_{i=1,2}\left(x_j-Q_{\theta i}\left(S_j,\text{Å}_j\right)\right)^2 \quad (42)$$

The soft update is carried out to update target neural network parameters. Similarly, the minimization of the loss function l_C and maximization of the loss function l_A It is carried out to perform the updation of online Q-value parameters and online policy network parameters, respectively. The updation processes can be formulated as,

$$\begin{cases}\phi'\leftarrow t\phi+\left(1-t\right)\phi' \\ \hat{\theta}i\leftarrow t\hat{\theta}i+\left(1-t\right)\hat{\theta}i\end{cases} \quad (43)$$

This facilitates the agent to achieve optimal policy. Thus improves the tracking accuracy in the indoor environment.

V. Experimental study

The performance of the proposed VIRALTRACK model is evaluated, and simulation results are discussed. This section includes three subsections: simulation setup, comparative analysis and research summary.

4.5 Simulation setup

We design a 3-D grid network topology that includes four RFID readers, one centralized server, sixteen real/phy reference tags, thirty-two virtual reference tags, and one target tag. The proposed VIRALTRACK model is experimented with in 300 x 400 m simulation environment for RFID localization and tracking using intellectual techniques in the indoor environment. The simulation parameters are shown in Table 3. The system configurations are illustrated in Table 2.

Table 2: System specifications

Hardware Specification	Hard Disk	500GB
	RAM	4GB
	Network Simulator	NS3.26
Software Specification	Operating System	Ubuntu 14.04 LTS

Table 3: Simulation parameters

Parameters	Value
Network Parameters	
Area of simulation	300×400m
Topology	3D Grid network
RFID reader	4
Centralized server	1
Real/Phy reference tag	16
Virtual reference tag	32
Target tag	1
Channel frequency	915MHz
Fading	No

Inference of Inter channel	No
Data rate	2 Mbps
SNR-based signal reception	10
The transmission power of RFID	-45 dBm
Read range	1.62 m
Range of sensing	5.4 m
Range of inference	7.1m
Number of nodes	50
Control channel frequency	930 MHz
Radio Rx Sensitivity	-91 dBm
Sensitivity reader power	-70dBm
Sensitivity tag power	-17dBm
Transmission range	30m

Fig 5 represents the simulation environment of the proposed VIRALTRACK model, which considers the 3D grid topology. The proposed VIRALTRACK environment includes four RFID readers, one centralized server, 16 real/phy reference tags, thirty-two virtual reference tags, and one target tag.

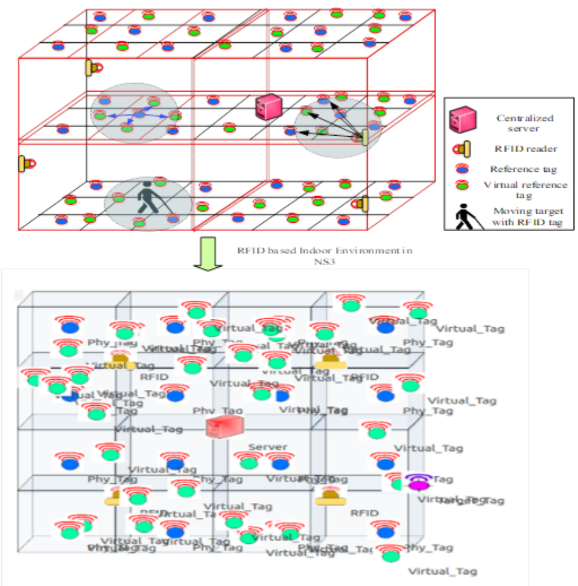

Figure 5: Simulation Environment of proposed VIRALTRACK model

And moving target with an RFID tag is also represented in the Fig. RFID readers have small coverage covering the number of virtual and reference tags. RFID reader is used to track the reference tags in an indoor environment.

Fig. 6 represents the target tag tracking process using the TD3 algorithm, performed by the centralized server by each reader positioned in the indoor environment. TD3 algorithm automatically learns the indoor environment and provides better tracking results, improving tracking accuracy.

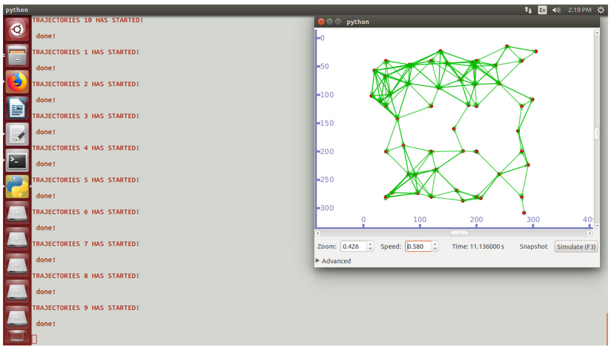

Figure 6: Target tag tracking process using TD3 algorithm

4.6 Use case

Indoor localization using RFID tags is predominantly used in smart home applications. The user's location information is gathered to make precise decisions in many cases. The advantages of RFID systems, such as non-LOS readability, contactless communication, increased data rate and security, have enabled its use in smart home applications. Further, the location information of users in the smart home facilitates the indoor navigation of elder age and visually impaired users.

Figure 7: Case diagram for an indoor scenario

Fig.7 depicts the use case diagram of RFID in the smart home in which the RFID reader is placed in the living room, which is responsible for tracking the location with the help of tags. The reference and virtual tags are placed in each room to transmit and receive radio signals with the moving target. For instance, the tags R1 to R4 are placed in the living room, R5 is placed in the portico, R6 and R7 are placed in the bedroom, R8 in the toilet, R9 in the Pooja room, R10 and R11 in the dining room, R12 in the store room and R13 in kitchen.

Table 4: RFID specifications

RFID model	RC522
Type	Active RFID
Frequency	902-928 MHz
Power source	External source
Read rate	400 tags/sec
Read range	4 to 7 meters
Memory size	64 to 2052 bits
Transmission speed	19300 bps
Temperature operated	-25° C to 55° C
Communication standard	USB
Output power	0.70mW

The specifications of the RFID communication are presented in Table 4. The signals acquired from the moving target are initially improved by using EGF to remove the fluctuations. Further, the placement of virtual tags in the 3D indoor environment by implementing EPC, which considers SNR, temperature and humidity for optimal solution. The tracking error is reduced by performing the initial localization of the moving target using the QNN model. Finally, the accurate tracking of the moving targets is performed by the centralized server using TD3.

4.7. Comparative analysis

This section evaluates the performance of the proposed VIRALTRACK model in terms of several performance metrics, such as tracking accuracy, tracking error and cumulative probability. From these performance metrics, we proved that our model work is better than existing models. The comparison analysis performs with the PSO-TRACK [36], MOIT [37] and proposed VIRALTRACK model.

4.7.1 Impact of tracking accuracy

This metric is used to evaluate the correctness of the proposed VIRALTRACK model. Tracking accuracy is calculated concerning the number of tags. Fig 8 compares tracking accuracy for both proposed and existing models. The comparison result shows that the proposed VIRALTRACK achieves high accuracy compared to other methods. And we proposed Extended Gradient Filter (EGF) to remove noise and RSSI fluctuations, increasing the tracking accuracy. In our method, we proposed optimization-based virtual tag allocation, which is used to optimize the virtual reference tag by considering SNR, many factors that affect the RSSI signal. Based on these factors, the RFID reader allocated the virtual tags that increase the tracking accuracy. And also, the proposed work performs Quantum based localization which selects the optimal virtual reference tag for localization. The optimal localization method increases the tracking accuracy and reduces the error during tracking. We proposed deep reinforcement learning-based tracking that learns the indoor environment and provides better tracking results, increasing tracking accuracy. The existing method does not perform optimal localization and tracking, which reduces tracking accuracy. The proposed VIRALTRACK method achieves 20% high accuracy than the MOIT method and 11% higher than the PSO-TRACK method.

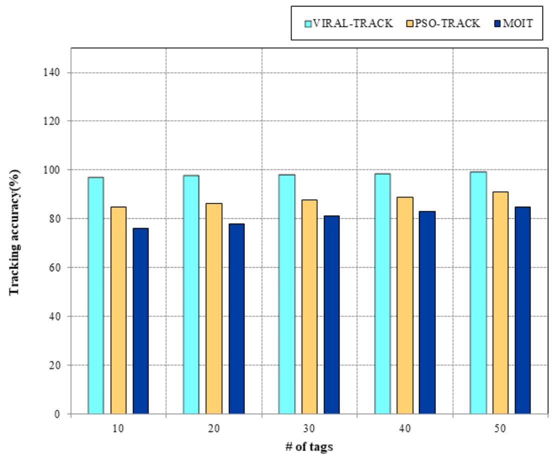

Figure 8: Tracking Accuracy vs. No. of Tags

Table 5 illustrates the numerical analysis of tracking accuracy concerning the number of tags. The table presents the average value of tracking accuracy. From the numerical analysis, the proposed VIRALTRACK model achieves high accuracy compared to others.

Table 5: *Tracking accuracy (%) analysis*

Method	# of tags
VIRAL-TRACK	98.02 ± 0.5
PSO-TRACK	87.82 ± 1.0
MOIT	80.6 ± 1.5

4.7.2 Impact of tracking error

This metric evaluates the errors during tracking due to random localization, noise, and multipath effects in an indoor environment. If the tracking error is high, the system will achieve poor accuracy. The tracking error is calculated concerning SNR, number of tags and trajectories.

Fig 9a compares tracking error for proposed and existing models for several tags. The comparison result shows that the proposed VIRALTRACK model achieves low tracking error compared to existing models. Because our proposed work performs optimal virtual reference tag allocation, which is used to reduce the interference created by the real reference tag. The virtual

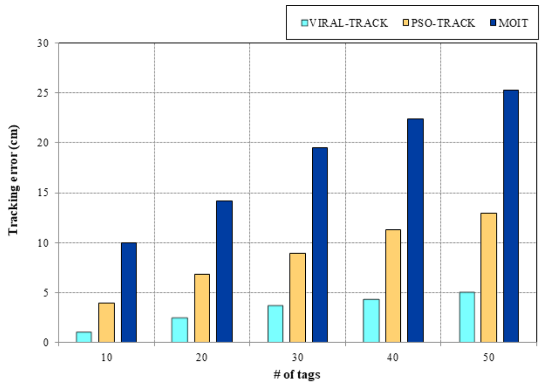

Figure 9a: Tracking error vs. No. of tags

reference tag is allocated by using Emperor Penguin Colony (EPC) algorithm, which optimally allocates the virtual reference tag, reducing tracking errors.

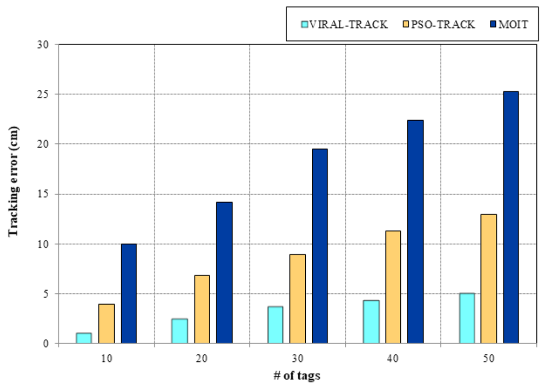

Figure 9b: Tracking Error vs. No. of trajectories

Then we perform Quantum based localization, which selects the optimal virtual reference tag localization, reducing tracking errors. To reduce tracking error, we proposed a deep reinforcement learning algorithm that learns the indoor environment automatically and takes action based on the current status of the environment, which reduces tracking error and increases tracking accuracy. The proposed VIRALTRACK model reduces by 15 cm lower than the MIOT model and 13cm lower than the PSO-TRACK model for the number of tags. Similarly, Fig 9b represents the comparison of tracking error for the number of trajectories. The result shows that the proposed VIRALTRACK model achieves less tracking error than the existing model by performing optimal localization and deep reinforcement-based tracking. The proposed VIRALTRACK reduces 18cm less than the MIOT model and 14cm less than the PSO-TRACK method.

Fig 9c represents the comparison of tracking error for SNR. The Fig. clearly states that the proposed VIRAL-TRACK model achieves less tracking error compared to the existing model by reducing the fluctuations of RSSI

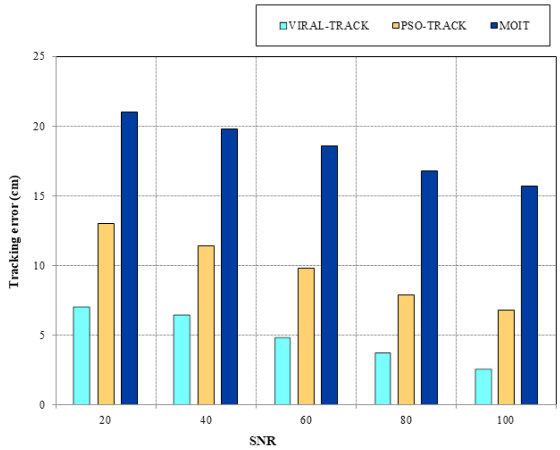

Figure 9c: Tracking Error Vs. SNR

signal using the Extended Gradient Filter (EGF), which increases single strength and reduces tracking error. And the optimal virtual tag allocation considers the SNR for calculating fitness value, thus reducing tracking errors. The proposed VIRALTRACK method achieves 13cm less than the MIOT model and 9cm less than the PSO-TRACK model. Table 6 illustrates the numerical analysis of tracking error, which shows the average value of tracking error for SNR, No. of tags and No of trajectories. From the numerical analysis, the proposed model achieves less tracking error than an existing model.

Table 6:*Tracking error (cm) analysis*

Method	SNR	# of tags	#of trajectories
VIRAL-TRACK	4.9 ± 0.05	3.8 ± 0.05	4.46 ± 0.05
PSO-TRACK	9.78 ± 0.10	8.8 ± 0.10	8.52 ± 0.10
MIOT	18.38 ± 0.15	18.28 ± 0.15	22.42 ± 0.15

4.7.3 Impact of cumulative probability

This metric is used to evaluate the cumulative probability during tracking. It is calculated based on the target positioning of the RFID tag. And also it refers to the probability that measures the odds of two or more events happenings during RFID localization and tracking in an indoor environment. Fig 10 represents the comparison of the cumulative probability of proposed and existing methods for SNR. The Fig. shows that the proposed VIRALTRACK model achieves high cumulative probability compared to existing works because our work achieves high probability for all four processes of RFID localization and tracking using intellectual techniques in an indoor environment. First, we proposed EGF to remove RSSI fluctuations, thus increasing tracking accuracy, which increases the probability value of signal power. Second, we proposed optimization-based virtual reference tag allocation, thus increasing the allocation probability of virtual reference tags by reducing the tracking error. And third, we proposed Quantum based localization, thus increasing localization accuracy and probability. Finally, we proposed deep reinforcement learning-based tracking, which reduces tracking error and increases tracking accuracy and probability. And the cumulative probability is calculated by adding the four process probability values. The four processes achieve high probability, and then the cumulative probability also achieves high probability compared to existing models.

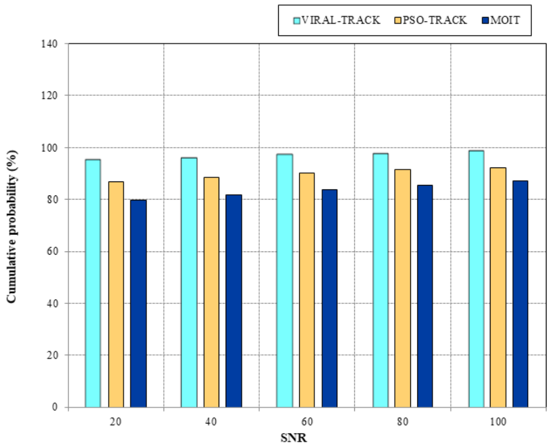

Figure 10: Cumulative Probability vs. SNR

Table 7 represents the numerical analysis of cumulative probability for SNR. The table illustrates the average value of cumulative probability. From the analysis, the proposed VIRALTRACK model achieves 14% higher than the MOIT model and 8% higher than the PSO-TRACK model.

Table 7. *Cumulative probability (%) analysis*

Method	# of tags
VIRAL-TRACK	97.08 ± 0.5
PSO-TRACK	89.76 ± 1.0
MOST	83.6 ± 1.5

4.7.4 Impact of true positive rate

This metric is used to calculate the accuracy of the RFID tracking system. TRP represent the proportion of the number of correctly identified virtual reference tag to the total number of virtual reference tag. It is calculated as follows,

$$TRP = \frac{\text{Ձ}}{\text{ʆ}} \quad (44)$$

Where TRP represents the true positive rate, Ձ represents the number of identified virtual reference tag and ʆ represents the total number of virtual reference tags.

Fig 11 compares the true positive rate for the proposed and existing models for motion speed. The Fig. clearly states that the proposed VIRALTRACK model achieves a high true positive rate compared to an existing model. In our method, we reduce RSSI fluctuations, improving signal strength and tracking accuracy. And also, deploy the virtual reference tags in indoor tracking, which reduces the interference created by the real reference tag, thus increasing tracking accuracy and true positive rate. QINN-based localization is performed to detect the initial position of the target tag. Then reinforcement learning-based tracking is performed to increase tracking accuracy, thus also increasing the true positive rate. In this way, we accurately track moving objects in an indoor environment, thus increasing the true positive rate.

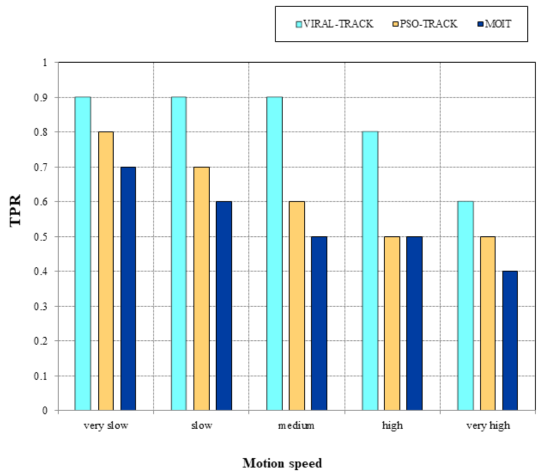

Figure 11a: True Positive Rate vs. Motion speed

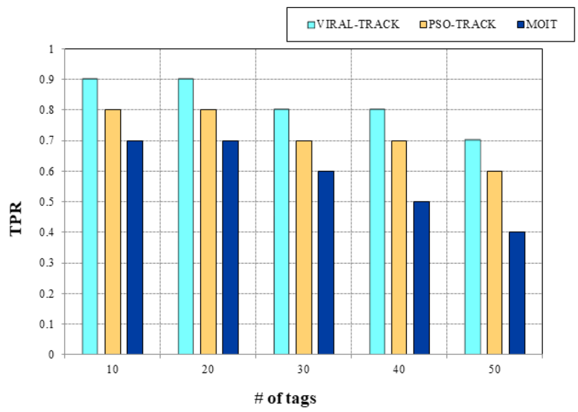

Figure 11b: True Positive Rate vs. Number of tags

Similarly, Fig. 11b represents the comparison of the true positive rate for both the proposed and existing model for some tags. The Fig. shows that the proposed VIRALTRACK model achieves a high true positive rate. The value of the true positive rate is increased exponentially with the increasing number of tags. The proposed VIRALTRACK achieves a high true positive rate by performing signal improvement, optimization-based virtual reference tag allocation, Quantum-based localization, and deep reinforcement learning-based tracking, which increases the true positive rate.

Table 8: *True positive rate analysis*

Method	Motion speed	# of tags
VIRAL-TRACK	0.82 ± 0.001	0.82 ± 0.001
PSO-TRACK	0.62 ± 0.005	0.72 ± 0.005
MIOT	0.54 ± 0.015	0.58 ± 0.015

Table 8 represents the numerical analysis of the true positive rate for motion speed and number of tags for both the proposed and existing models. The table illustrates the average value of the true positive rate. From the numerical analysis, the proposed VIRALTRACK achieves a high true positive rate.

The VIRALTRACK model presented in this study demonstrates superior performance compared to existing Radio Frequency Identification (RFID) localization and tracking models in indoor environments. The Extended Gradient Filter enhances received signals, significantly boosting tracking accuracy. An optimization-based virtual reference tag allocation minimizes interference from multiple real reference tags, further refining system performance. Quantum Neural Network-based Localization accelerates initial position estimation, providing optimal results in moving object localization. The Tracking and Detection Dimensional Deep Deterministic Policy Gradients (TD3)-based learning algorithm ensures accurate tracking of moving targets by leveraging RFID reader information. Through signal improvement, optimized tag allocation, quantum-inspired techniques, and deep reinforcement learning, the VIRALTRACK model represents a notable advancement in RFID-based localization and tracking, promising enhanced accuracy and adaptability in dynamic indoor settings.

5 Conclusion

This paper proposes VIRALTRACK, a novel system designed for Radio Frequency Identification (RFID) localization and tracking within indoor environments. The primary objective is to enhance tracking accuracy and minimize errors during the tracking process. An innovative Extended Gradient Filter (EGF) algorithm is proposed to refine signal strength by reducing Received Signal Strength Indication (RSSI) fluctuations. The deployment of virtual reference tags, managed by the Emperor Penguin Colony (EPC) optimization algorithm, addresses challenges associated with real reference tags in RFID tracking systems, ultimately augmenting tracking accuracy. The subsequent step involves target moving tag localization, employing a Quantum-inspired Neural Network (QNN) for precise position estimation and error reduction during tracking. The final stage incorporates a deep reinforcement learning-based tracking mechanism utilizing the Twin Delayed Deep Deterministic Policy Gradient (TD3). This comprehensive approach significantly enhances tracking accuracy within the specified environment. The VIRALTRACK model's performance is evaluated based on tracking accuracy, tracking error, and cumulative probability, positioning it as a promising advancement in RFID-based localization and tracking. Future work aims to address the impact of moving target shadows on RSSI signal quality and explore multi-target localization to further enhance overall efficiency.

6 Conflicts of interests

The authors have no Conflicts of interests/Competing interests to disclose.

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Arrived: 24. 07. 2023
Accepted: 02. 02. 2024