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Reliable Multi-Object Tracking Model Using Deep Learning and Energy Efficient Wireless Multimedia Sensor Networks

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ABSTRACT Presently, sensor-cloud based environment becomes highly beneficial due to its applicability in several domains. Wireless multimedia sensor network (WMSN) is one among them, which involves a set of multimedia sensors to collect data about the deployed region. Compared to traditional object tracking models, animal tracking in WMSN is a tedious process owing to the harsh, dynamic, and energy limited sensors. This article introduces a new Reliable Multi-Object Tracking Model using Deep Learning (DL) and Energy Efficient WMSN. Initially, the fuzzy logic technique is employed to determine the cluster heads (CHs) to attain energy efficiency. Next, in the second stage, a novel tracking algorithm by the use of Recurrent Neural Network (RNN) with a tumbling effect called RNN-T is developed. The proposed RNN-T model gets executed by every sensor node and the CHs execute the tracking algorithm to track the animals. Finally, the tracking results are transmitted to the cloud server for investigation purposes. In order to assess the performance of the presented model, an extensive experimental analysis is carried out by the use of a real-time wildlife video. The obtained results ensured that the RNN-T model has achieved better performance over the compared methods in different aspects.

INDEX TERMS WSN, clustering, deep learning, tracking, energy efficiency, sensor cloud.

I. INTRODUCTION

Wireless Multimedia Sensor Network (WMSN) includes a set of compact-sized, autonomous, energy limited, and distributed multimedia sensors which can transmit the multimedia data using wireless links. In WMSN, the sensor nodes are linked to the camera to sense and capture the multimedia data [1]. It finds use in several fields in the surveillance and tracking actions such as healthcare, habitat surveillance, military, etc [1]. In general, the sensor nodes are deployed in the harsh environments such as deep forest, hill, or buildings for monitoring or detecting particular events [2]–[4]. The usage of WMSN for surveillance application areas offers a method of monitoring environmental activities like volcanoes, forest fire, landslide, etc [5], [6]. The usage of WMSN in remote areas will be highly beneficial since it is very tedious to observe it because of the problematic and inhabitable situations for humans. Wildlife monitoring is one of the critical areas in this field. It has attracted more researches due to the high forest depletion and extinction of rare species. It paves a way to save animals by observing the behavior and other parameters of a given species.

Habitation and ecological monitoring denote a kind of WMSN applications which is advantageous to scientific communities and societies [7]. This technology enables the research people and biologists to thoroughly analyze the target region [43] by giving the local measurements, sampling, and in-depth information, which are usually hard and high cost to get. The conventional methods to obtain the data always need a person for monitoring the target area, which

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may disturb the nature of animals. For instance, [9] seabird colonies are very delicate and sensitive to human existence. In Maine, scientists identified that the visit of 15minutes every day to the seabird colonies had raised the egg as well as chick death rate by 20% within a specified breeding period. When it gets disturbed repeatedly, the whole colonies will ditch the site to carry out the breeding process. Several works have been carried out to track the motion of animals in their living area [10]–[15].

The domain of animal tracking became familiar in the past decade because of government actions to track livestock in the country [10]. A ecognition model is also developed to place an RFID chip into the animals by the use of syringes, usually in the size of rice grain. In Maine's Great Duck Island (GDI) [11], scientists deployed sensor nodes in the downsized of the duck nests and on four edges immediately exterior of duck burrow for a time duration of nine months. This network of a total of 32 nodes regularly streams data into the internet. In Princeton University [12], the advancement of WSN is investigated and employed to track wildlife for biological study. This tracking model, known as ZebraNet which sends the details to the base station (BS). The sensors weigh around 1kilogram, and GPS is also used. Several tracking methods are also present for tracking the targets in motion [13]–[15]. Scientists have modeled the computation of signal obtained from the sensor to calculate the time-dependent measurement for identifying the position and nature of the tracking animals. A distributed target tracking technique in WSN has been introduced in [16]. This algorithm clusters the sensor and triplet triangulation is employed for the prediction of the target location. Then, a linear predictor using the previous two target positions is used to predict the next target.

On the other hand, low power, persistent computing [17] becomes an increasingly feasible model for diverse applications like a visual tracker. The idea is to frequently calculate the location and features of the target inside a region. When employed to WMSN, the primary issue lies in the fact of energy efficiency. The sensor nodes in WMSN have constraints on energy, bandwidth, and memory. To assist in the scenario of energy-constrained system, the main intention is to make use of the available energy efficiency and to enhance the lifetime of WMSN. Since maximum energy is spent on data transmission compared to sensing and processing operations, the reduction in energy consumption on transmission efficiently minimizes the overall energy utilization of the WMSN.

The tracking of animals in forest involves several difficulties like a) no information about the unidentified targets, b) uninterrupted state computation of every available target, and c) harsh environment. This article presents an end-to-end learning method for multi-target tracking. The presently available deep learning (DL) approaches are not developed for the difficulties mentioned above and cannot be straightly employed in the process. The RNN has the natural ability of self-learning process using the portion of an input sequence. Initially, in the training phase of RNN-T, the target coordinates in the image sequences are read and checks whether the target coordinates are static. When the target coordinates are not static, then it is considered that the object is in motion. In the training phase of RNN-T algorithm, the tumbling effect will also operate. The tumbling effect helps to learn the actions of moving around in different directions. The efficient self-learning capability of RNN with the tumbling effect makes the training phase effective [42], [43]. In the testing phase, the RNN-T algorithm compares the target correlation, and movement is tracked when the difference in target correlation exists.

Though several tracking models are available in the literature, there is an absence of energy efficiency with tracking algorithm, particularly for tracking animals. This article proposes an energy efficient cluster-based tracking algorithm for efficient animal tracking. The proposed method operates on two stages: fuzzy based clustering algorithm and effective tracking algorithm using Recurrent Neural Network (RNN) with a tumbling effect named as RNN-T, which shows the novelty of the work. For satisfying the practical considerations of energy efficiency issues in WMSN, a fuzzy logic based clustering technique is also presented. The proposed RNN-T mechanism will be embedded in every node present in the WMSN. Every node will start tracking the animals using the presented method. After tracking, the sensor node has to transmit the data to the base station. The clustering technique achieves energy efficiently by effectively handling data transmission between sensor nodes and BS. By the use of the clustering technique, the tracked data can be effectively communicated. Several performance measures like tracking error and average energy utilization are used to investigate the results obtained from experiments to calculate the effective outcome of the research. In short, the contribution of the paper is summarized as follows.

- Propose an energy efficient cluster-based tracking algorithm for efficient animal tracking.
- The proposed method operates on two stages: fuzzy based clustering algorithm and RNN-T based tracking algorithm.
- The proposed method is placed on every node to track the animals
- After tracking, the sensor node has to transmit the data to the base station.
- Validate the performance of the proposed method interms of different measures.

The following portion of the paper is arranged below: Section 2 outlines the different object tracking approaches. The proposed cluster-based tracking algorithm is elaborated in section 3. The validation of the presented method using different video sequences are done in Section 4, and the concluding annotations are provided in Section 5.

II. RELATED WORKS

Numerous target tracking models have been developed to handle the obstacles that exist in the real-time deployment [18]–[29]. In [30], a particle swarm optimization (PSO) based object tracking technique is developed for image sequences. During the initialization of every frame, the particles are derived from a Gaussian distribution to pack up the important object location. Due to the dynamic behavior of object tracking problem based on the object state and time, a sequential particle swarm optimization (SPSO) technique is projected in [31], which integrates the temporal continuity data to the conventional PSO algorithm.

The authors in [32] presented a tracking method named IS-Obj Track which uses the PSO algorithm to achieve robust and faster results. The benefit of the IS-Obj Track is the use of a histogram of oriented gradients (HOG) in the design of object appearance design. A multi-target tracking algorithm with the help of the PSO algorithm is devised in [33]. At the starting of every frame, the target objects are tracked separately by the use of highly discriminative appearance models among various targets. Every individual target is being tracked using separate PSO algorithms. For increasing the speed of the tracking process, the PSO algorithm is used for tracking [34]. This algorithm enables the system to track objects with fewer hardware needs. The output from the PSO algorithm generally holds less noise. For eliminating noise and computation of the trajectory of the object, the Kalman filter is used. [35] presented a new object tracking method using Dominant points on tracked objects by employing the Quantum particle swarm optimization (QPSO) algorithm.

The fascinating characteristic of the QPSO is the nature of adaptability to the variable as well as and static background. [36] presented a visual tracking method to study the intelligent nature of fishes which is observed in the experiments by catching fish. This visual tracking system uses the global as well as local searching features of the genetic algorithm. A harmony filter using a harmony search algorithm is presented in [37] for visual tracking. A firefly (FF) based tracking algorithm is introduced in [38] and is employed for multiple objects tracking in [39]. FF algorithm contains some features like the PSO algorithm with better performance in optimization problems. In this method, the similarities between the primary objects window and secondary objects window in every frame are chosen as the objective function. This article employed the behavior of bats to search targets in a series of images. A bat algorithm (BA) based tracking model [40] is introduced, where the sensitivity and parameter adjustment in BA is also investigated.

An extensive survey has been made of the modern state of art methods, and it has been concluded with the need for having an improved tracking algorithm to enhance tracking accuracy and reduce energy consumption. Though many methods consider that significant resources are available at every node, efficient techniques need to be developed with high tracking accuracy and low energy utilization. Clustering in WMSN is found to be an energy efficient technique commonly employed in a different scenario [1], [2]. Though different tracking methods exist, there is still a way to boost the overall results of the model. Besides, in contrast to vehicles or other tracking objects, the animals have the natural tendency to move around in different directions rapidly. Most of the existing tracking algorithms fail to track when they turn around quickly.

TABLE 1. The Parameters and Their Possible Values.

Input parameter	Remaining energy	Low(L), Medium(H), High(H)
	Distance to predicted location	Nearby(N), eachable(R), Far(F)
Output parameter	PBCH	Very Low (VL), Low(L), Rather Low(RL), Low Medium(LM), Medium(M), High Medium(HM), Rather High(RH), High(H), Very High(VH)

III. THE PROPOSED ALGORITHM

The proposed cluster-based tracking algorithm incorporates two main phases namely fuzzy logic based clustering algorithm and RNN-T based animal tracking algorithm. In the first phase, fuzzy logic performs clustering and selects CHs by employing two input variables namely, remaining energy and predicted distance to the target location. Once the clusters are formed, every node will execute the RNN-T algorithm to track the animals efficiently. After some predefined rounds of the tracking process, the captured video will be sent by the cluster members to CHs [18]. Then, the CHs will transfer data to BS via intermediate CHs. The two phases of the proposed algorithm are discussed in the subsequent subsection.

A. FUZZY LOGIC BASED CH SELECTION

Presently, fuzzy logic has been finding useful in different areas because of its merits like low computational time, flexible, low cost, low storage space, and fault tolerance [8]. After the deployment of WMSN nodes, each node will execute fuzzy logic and determines the probability of becoming CH (PBCH). The operation of fuzzy logic [41] comprises the following four steps:

i) Fuzzification: Converting the crisp inputs to fuzzy inputs by mapping it to suitable linguistic variables
ii) Membership Function (MF): Triangular and Trapezoidal MF
iii) Rule base: The input variables are linked by a collection of if-then rules using linguistic variables.
iv) Defuzzification: Conversion of a fuzzy output parameter to a crisp value.

The proposed method employs two input parameters namely distance to the predicted location and the outstanding energy of the node to perform clustering in the network.

1) FUZZIFIER

The input variables are residual energy and distance to the predicted location. Using the given fuzzy parameters, the given inputs are mapped to produce fuzzified inputs. The linguistic variables of the input in addition to output variables are given in Table 1.

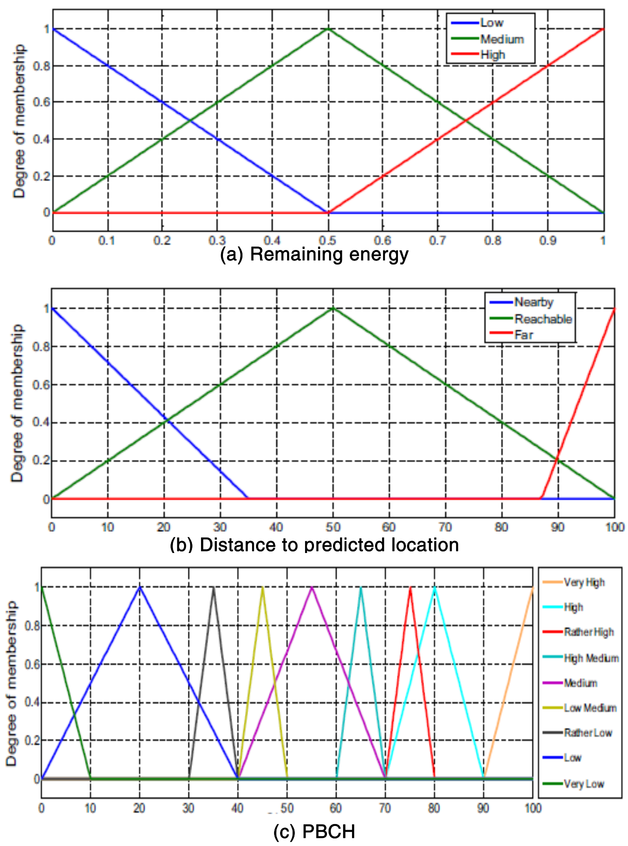

FIGURE 1. **The membership functions.**

2) MEMBERSHIP FUNCTIONS

The trapezoidal MF is employed for boundary variables (L, H, N, F, VL, VH, VS, and VL) and triangular MF is employed for the intermediate variables. The MF of the input and output variables as given in Fig. 1. And, the two triangular and trapezoidal MFs are specified in Eq. (1) and Eq. (2).

$$\mu_{A1}(x) = \begin{cases} 0 & x \leq a \\ \dfrac{x-a}{b-a} & a \leq x \leq b \\ \dfrac{c-x}{c-b} & b \leq x \leq c \\ 0 & c \leq x \end{cases} \tag{1}$$

$$\mu_{A1}(x) = \begin{cases} 0 & x \leq a \\ \dfrac{x-a}{b-a} & a \leq x \leq b \\ 1 & b \leq x \leq c \\ \dfrac{d-x}{d-c} & c \leq x \leq d \\ 0 & d \leq x \end{cases} \tag{2}$$

3) RULE BASE TABLE

A rule base table is a group of if-then rules used to correlate the input to output parameters by employing the linguistic variables. A rule can be represented as follows.

$$Rule\ (i)\ IFx_1\ is\ A_1^i\ AND\ x_2\ is\ A_2^i\ THEN\ y_1\ is\ B_1^i \tag{3}$$

TABLE 2. **The Set of Fuzzy Rules.**

Remaining energy	Distance to predicted location	PBCH
L	N	RL
L	R	L
L	F	VL
M	N	HM
M	R	M
M	F	LM
H	N	VH
H	R	H
H	F	RH

where i is the ith rule in the rule table, A1, A2and B1 is the fuzzy set of x1, x2. Since the number of inputs is 2, there are nine rules are required as provided in Table 2. They are produced through Mamdami inference system [41]. To attain maximum chance of elected as CH, the residual energy should be high, and Distance should be low.

4) DEFUZZIFICATION

Centroid of Area (COA) scheme is employed to defuzzify the input using the Eq. (4). It transforms the output in a fuzzy form to the original input value representing the possibility of a node to become a CH and its cluster size.

$$COA = \frac{\int \mu_A(x)\,.xdx}{\int \mu_A(x)\,.dx} \tag{4}$$

Once every node computes the value of PBCH, the information will be exchanged among the neighboring nodes. The node with the higher value of PBCH will be elected as CHs, and the nearby nodes will be joined to the CH to form clusters. When the clustering process is completed, the tracking algorithm will be executed.

B. RNN-T BASED TRACKING ALGORITHM

The overall operation of the RNN-T method is displayed in Fig. 2 and the algorithm is given in Algorithm 1. Initially, the sequence of frames in the video will be extracted. Next, the frames undergo the training process using RNN-T algorithm, and then the target will be represented. Next, the target values are noted down to compute the coordinates. Once the coordinates are determined, the past and present target coordinates will be compared to one another.

When any of the differences exist, it is assumed that the target object is in movement. After the completion of the training process, the testing phase will be carried out. During this process, multiple targets in the video can be easily captured. Furthermore, the inclusion of a tumbling effect will help to improvise the accuracy of the tracking method. The tracking of the RNN-T model involves two main functions: The tumbling process and tracking of target motion. These two phases are discussed in the following subsections.

1) TUMBLING EFFECT

The bacteria movement in the intestine while searching the locations of rich nutrients away from the harmful environment is done by the use of locomotory organelles called

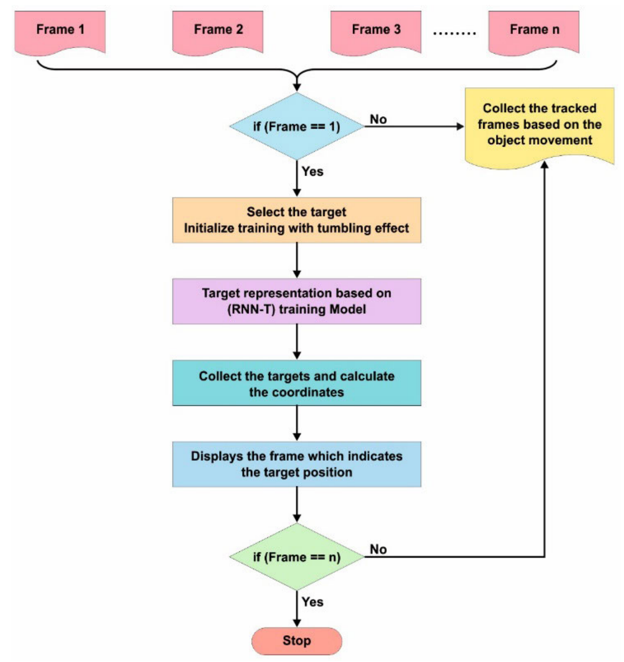

FIGURE 2. The flowchart of RNN-T algorithm.

flagella through swimming or tumbling (traveling in the exact opposite direction from the preceding one).In the RNN-T, the choice of animal movement is finalized by the value of fitness function. When the animal travels normally, then conventional RNN can track it. By contrast, when the animal rapidly moves around in a different direction, the RNN follows the chemotactic movement of the bacterium. It is represented in Eq. (5), which calculates the output given in Eq. (6).

$$\mathrm{H_t} = \mathrm{H_{t-1}} + \mathrm{H_t} \times \frac{\Delta \mathrm{H_t}}{\sqrt{\Delta^{\mathrm{T}}}} \tag{5}$$

$$\mathrm{O_t} = \sigma_\mathrm{o}(\mathrm{W_o H_t} + \mathrm{B_o}) \tag{6}$$

where Δ^T is the randomly generated number between $[-1, 1]$, H represents the hidden layer and O represents the output layer. The tumbling indicates the animal travels in diverse directions (opposite direction) from the preceding direction. Chemotactic movement of RNN will be continued until the RNN tracks the direction of its target. This concept implies that the tumbling effect enables the RNN to improve the exploration of the available solution space. With the help of the tumbling process, the efficiency of the RNN based tracking process can be improved.

2) TARGET MOTION

The concepts of state prediction and update are explained here. The temporal RNN is employed for the learning of targets and indicators to decide birth and death of targets. At a time t, the RNN outputs four values for the next time step. A vector $x^*_{t+1} \in R^{N.D}$ predicted states for every target, a vector $x_{t+1} \in R^{N.D}$ of every updated state, a vector $\varepsilon_{t+1} \in (0,1)^{\mathrm{N}}$ of probabilities representing that every target how probable it is a real trajectory, and ε^*_{t+1}, which is the absolute difference to ε_t. This decision is determined using

Algorithm 1 RNN-T Algorithm

Input: $Img_i\,[X]\,[Y]$ – Images with target values in each cell of co-ordinates (x, y)
$i \in Training\ set\ images$
$H\ (n) - Hidden\ Layers$
$C\ (n) - Context\ Layers$
$O - Output\ Layer$
$t = 1$
//For Training
$\forall i \in Frames$ do
$\forall X \in x$ do
$\forall Y \in y$ do
$H_t = \sigma_h(W_t Img_t + U_h H_{t-1} + B_h)$
// Tumbling Effect
$H_t = H_{t-1} + H_t \times \frac{\Delta H_t}{\sqrt{\Delta^T}}$
End
End
End
//For Output targets
$\forall i \in Frames$ do
$\forall X \in x$ do
$\forall Y \in y$ do
$O_t = \sigma_o(W_o H_t + B_o)$
End
End
End
$t \leftarrow t + 1$
until $(Max_{Iteration} \geq t)$
//For Testing
$\forall i \in Frames$ do
$\forall X \in x$ do
$\forall Y \in y$ do
$H_t = \sigma_h(W_t Img_t + U_h H_{t-1} + B_h)$
$O_t = \sigma_o(W_o H_t + B_o)$
End
End
End
Output: Tracked Animals

the present state x_t, existence probabilities ε_t, measurements z_{t+1} and data association A_{t+1} in the subsequent frames.

There are three main objectives involved here:

1) Prediction: Learns the complex dynamic model to predict target motion in the absence of measurements.
2) Update: Learns to correct the state distribution, specified target-to-measurement assignments.
3) Birth/death: Learns to recognize tracking initiation and termination by the state, the measurements along with the data association.

The prediction x^*_{t+1} for the subsequent frames are mainly based on the present state x_t and the network's hidden state h_t. When the data association A_{t+1} for the upcoming frame is present, the state is updated based on the assignment probabilities. Finally, every measurement and the predicted state be concatenated to form $\hat{x} = \left[z_{t+1}; x^*_{t+1}\right]$ indicating that

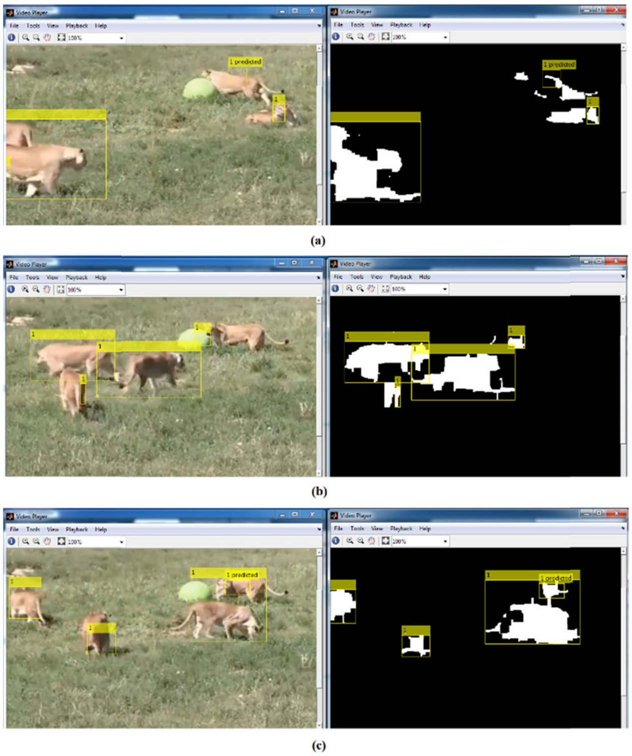

FIGURE 3. The visualization of proposed RNN-T animal tracking system for three frames.

weighted through the assignment probabilities A_{t+1}. It has been followed for every state dimension. In parallel, the track existence probability ε_{t+1} for the subsequent frames is also determined.

IV. PERFORMANCE EVALUATION

The cluster-based RNN-T model is implemented in MATLAB2014a. For experimentation, we have collected a sequence of videos and fivefold cross validation process is utilized. For experimentation, the parameters used are batch size:8, learning rate: 0.02, epoch, or step size: 10000, score threshold:0.7, minimum dimension: 600 and maximum dimension: 1024. The proposed algorithms employ different performance measures such as tracking accuracy and average energy consumption to validate the results.

A. MEASURES

The measures employed to examine the efficiency of the cluster-based RNN-T model are defined as follows:

Tracking error: It is computed using the tracked results and the ground truth using the Euclidean distance. For every testing video series, the average tracking error is defined as,

$$\bar{x}_{error} = \frac{1}{N}\sum_{t=1}^{N}\left\|x_t - \hat{x}_t\right\|^2 \tag{7}$$

where x_t and $\hat{x}_t$ are the values of the target and ground truth values. The value of tracking error should be as low as possible for effective tracking algorithm.

Energy consumption: This measure evaluates the amount of energy consumed by every node over the operational period.

First Node Die (FND): It denotes the round number at which the first node in the network completely exhausts its energy.

Half Node Die (HND): It denotes the round number at which 50% of the total nodes in the network exhaust its energy.

Last Node Die (LND): It denotes the round number at which all the nodes in the network exhaust its energy. It can also be used to identify the total amount of time the network is active.

B. RESULTS AND DISCUSSION

Fig. 3 provides the visualizations of some target identification by the proposed RNN-T algorithm for three frames. Next, an essential issue in the identification of a moving object is out of

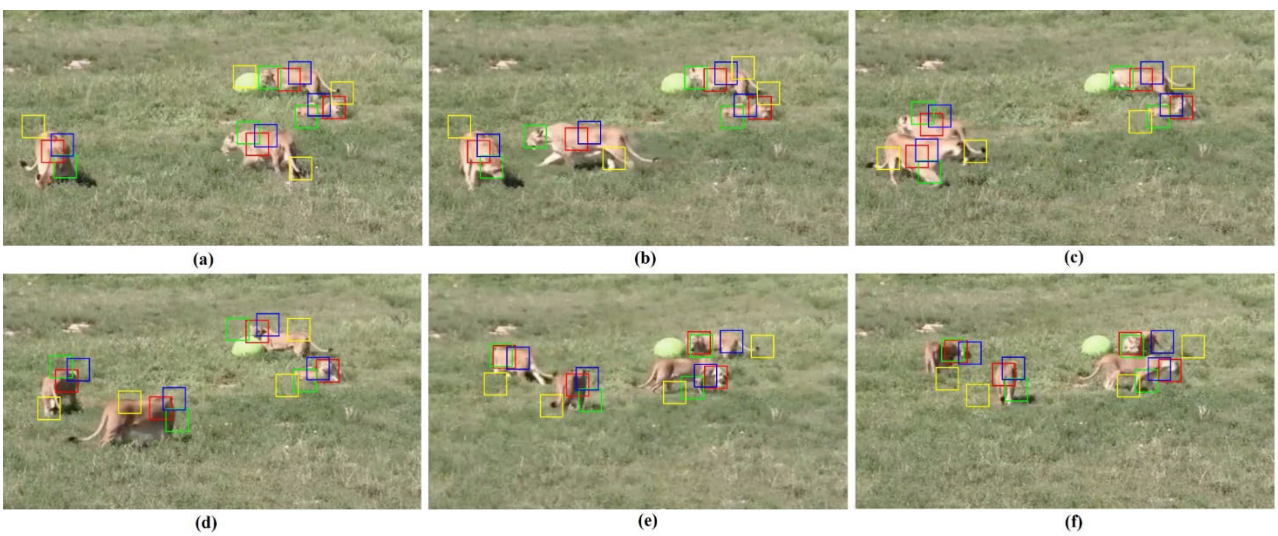

FIGURE 4. The multiple animal tracking performances on six test sequences [Red- RNN-T algorithm, Blue- Bat algorithm, Yellow- STC algorithm, Green-PSO algorithm].

FIGURE 5. The accuracy improvisation by the tumbling effect in RNN [Red- RNN-T algorithm, Blue- Bat algorithm, Yellow-STC algorithm, Green-PSO algorithm].

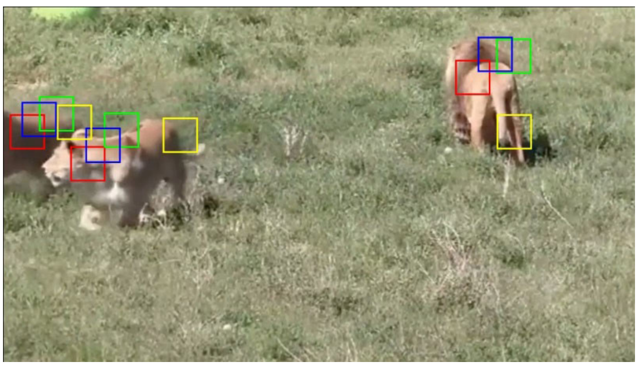

FIGURE 6. The out of frame detection [Red- RNN-T algorithm, Blue- Bat algorithm, Yellow- STC algorithm, Green-PSO algorithm].

frame detection. The RNN-T algorithm efficiently tracks the animals until the animal present in the frame. An illustration to verify the out of frame detection is shown in Fig. 4. Besides, a pictorial representation of different tracking algorithms is represented in Fig. 5. From this figure, it is clear that the RNN-T algorithm efficiently tracks multiple animals compared to other algorithms. Furthermore, the verification of accuracy improvisation by the inclusion of the tumbling effect in the proposed method is given in Fig. 6. As shown in the figure, the animals move around rapidly, and the existing methods fail to track properly whereas the existing method efficiently tracks all the animals consecutively.

The comparative analysis of proposed and existing methods is provided in Fig. 7, which illustrates the effectiveness of different tracking models like BA, PSO, and spatio-temporal context (STC) methods in terms of tracking error. The figure showcased that the PSO algorithm attained the worst performance among all the compared methods. Next, the STC method manages to outperform PSO but fails to show better tracking results over the bat and RNN-T algorithms. The STC algorithm obtained a lower error rate compared to STC and PSO algorithms. But, the proposed RNN-T algorithm was found to be superior to all the compared ones. The lowest value of error rate by the proposed RNN-T algorithm implies better tracking accuracy over several rounds. This is due to the inclusion of the tumbling effect in the tracking process. The moving around the behavior of the animals is not considered in the existing methods which lead to a higher error rate compared to the RNN-T algorithm.

Next, to analyze the energy-efficient capability of the cluster based RNN-T method, the average energy utilization, number of alive nodes, number of dead nodes, and number of CHs, as provided in Fig. 8. From the figure, it is showcased that the presented model has consumed lesser energy at the initial iterations and gradually increased with an increased number of iterations. The inclusion of the clustering process minimizes the overall energy utilization and also enhances the network lifetime.

Additionally, the network lifetime is measured concerning FND, HND, and LND. The comparison results of FND, HND, and LND of the RNN-T technique is displayed in Fig. 9. From the figure, is clearly shown that the FND of RNN-T with and without clustering are 1246 and 689, HND is 1817 and 1021, and LND is 2814 and 1897 respectively. From these values, it is clear that the network becomes inactive at the 2814 round by the cluster based RNN-T algorithm whereas the network becomes inactive in the 1807 round itself. From the obtained alues, it is apparent the cluster mechanism helps to improve the lifetime of the network significantly.

From the above mentioned experimentation, it is evident that the presented model has achieved reliable, robust, and energy efficient performance with a maximum tracking rate. The application of fuzzy logic and tumbling effect results to

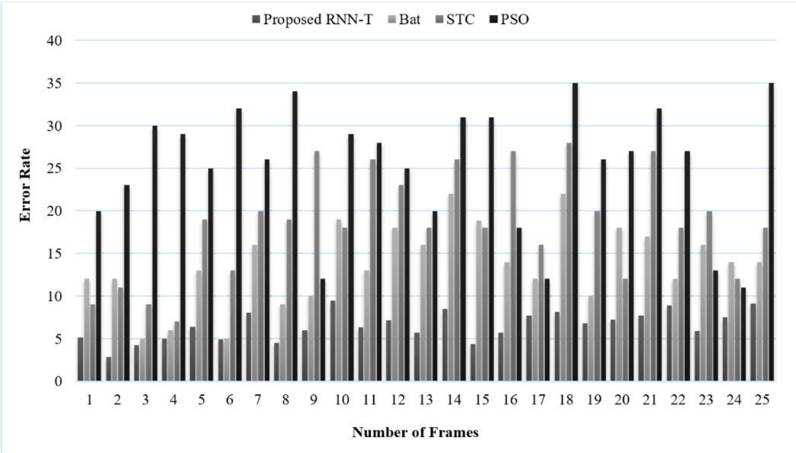

FIGURE 7. The comparison of various tracking algorithms in terms of error rate.

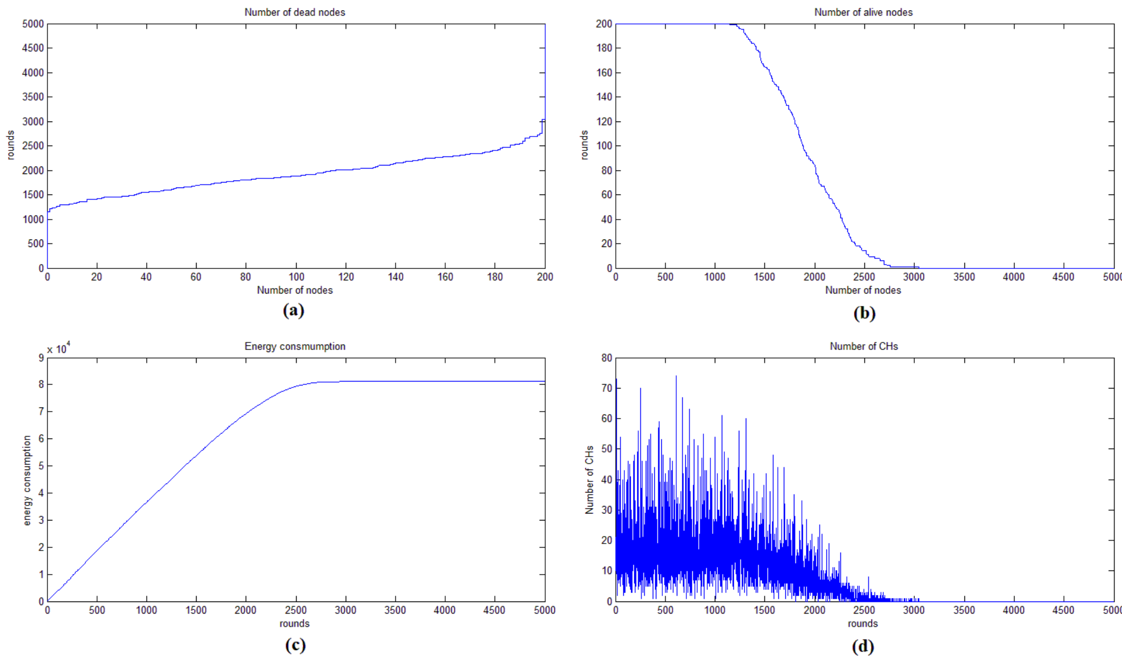

FIGURE 8. The energy efficiency and network lifetime analysis of the proposed method.

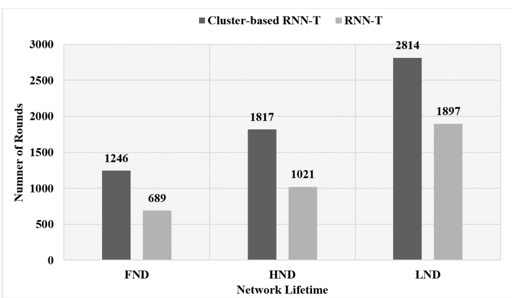

FIGURE 9. The network lifetime analysis.

better performance. Therefore, it can be employed as a real time tracker in any sensor-cloud based applications.

Table 3 investigates the computation time (CT) incurred by the presented and existing methods. The table values indicated that the RNN-T algorithm has obtained a minimum CT of 25s whereas the Bat, STC, and PSO algorithms required a maximum CT of 39s, 34s, and 31s respectively.

TABLE 3. Computation Time Analysis.

Methods	CT (s)
RNN-T	25
Bat algorithm	39
STC	34
PSO	31

V. CONCLUSION

This article has proposed an efficient cluster-based RNN-T algorithm for effective animal tracking. The proposed tracking algorithm incorporates two main phases namely fuzzy logic based clustering algorithm and RNN-T based animal tracking algorithm. In the first phase, fuzzy logic produces clusters and selects CHs using two input variables namely, remaining energy level and predicted distance to the location. Once the clusters are formed, every node will execute the RNN-T algorithm to track the animals efficiently. The proposed RNN-T exhibits effective tracking performance and the clustering technique enhances the network lifetime from 1897 rounds to 2814 rounds. From the observed experimentation, it is verified that the proposed method is superior to compared methods in a significant way. In future, the proposed can be extended to consider the camera movements, positions, noise, and so on. Besides, the energy efficiency can be further improved using data aggregation techniques.

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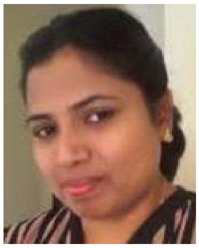

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