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ORIGINAL RESEARCH

Raccoon optimization algorithm-based accurate positioning scheme for reliable emergency data dissemination under NLOS situations in VANETs

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Abstract

In emergency situations, cooperative positioning of vehicular nodes is essential for facilitating precise and stable information for achieving reliable data dissemination in Vehicular Ad hoc NETworks (VANETs). However, the existence of Non-Line-Of-Sight (NLOS) nodes degrades the accuracy in estimating ranging measurements introduced by the blockages from tall vehicles and buildings. In this paper, Raccoon Optimization Algorithm-based Accurate Positioning Scheme (ROA-APS) is proposed for improving the accuracy in the estimation of ranging measurements in order to determine the exact position of NLOS nodes. It is proposed for ensuring maximized reliability and reduced latency in the event of warning message exchange. It inherits the food rummaging style of real raccoons for speeding and strengthening the local and global search process involved in the estimation of NLOS node positions. It utilizes maximum probability of acquiring higher adaptability through active learning to attain better localization of NLOS nodes. It inherits the distance information for calculating the position accuracy associated with vehicle trajectory, distance information error and the number of vehicles. It also uses the method of weighted average to enforce more confidence to the distance information provided by neighboring nodes. The simulation experiments of the proposed ROA-APS using EstiNet simulators are conducted to determine its significance with respect to positioning accuracy, emergency message dissemination rate, positioning error, neighbor vehicles awareness rate and positioning time. The results confirm an increased mean emergency message dissemination rate, positioning accuracy and neighbor vehicles awareness rate by 16.21%, 14.38% and 15.16% when compared to the benchmarked schemes.

Keywords Raccoon Optimization Algorithm (ROA) · Non-Line-Of-Sight (NLOS) nodes · Vehicular Ad hoc NETworks (VANETs) · Cooperative positioning · Emergency message dissemination

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1 Introduction

Vehicular Ad hoc NETworks (VANETs) are generally deployed for facilitating communication between collections of vehicular nodes based on the utilization of ad hoc wireless equipments (Wang et al. 2003). VANETs are nowadays used for a diversified number of applications that includes user-associated services, traffic management and safety services (Venkatraman et al. 2004). In particular, Vehicle-to-Vehicle (V2V) communication leverages each vehicle to generate a warning message in response to a critical event predicted in real-time (Amuthan and Kaviarasan 2018). This prediction of emergency events necessitates precise localization information for supporting critically safe real-time applications during vehicle accidents for helping the drivers in making reactive decisions (Amuthan and Kaviarasan 2019a, b). The determination and exchange of precise information about the location of vehicles during warning message transmission are considered as a limitation that needs to be addressed significantly (Muller et al. 2016). Vehicles are generally incorporated with Global Positioning System (GPS) equipments that help in estimating their precise location information in emergency situations (Qin et al. 2010). However, GPS may turn into an inaccurate device in estimating precise location information, since it may be impacted by the existence of NLOS situations that are introduced by tall buildings, vehicles and trees in dense urban areas that comprises of indoor packing lots and street canyons which are devoid of direct satellite visibility (Aadil et al. 2016).

The vehicle communication is always vulnerable to interference of signal as the vehicular nodes move in different patterns depending on environmental conditions (Boukerche et al. 2008). The construction sites and physical objects existing on the road sides (i. e., area topography, tress and buildings) have the probabilities of interfering with the radio signals, thereby resulting in the prevention of proper communication (Alam et al. 2013). This signal interference creates a state of Non-Line-Of-Sight (NLOS) to vehicular nodes which induces the drivers to make poor decisions when they merge onto a highway or change lanes (Hu et al. 2016). NLOS nodes are categorized into intentional and unintentional groups. The intentional NLOS nodes are formed when fake positions and malicious attacks are launched by the intruders on the vehicular network (Cruz et al. 2017). The unintentional NLOS nodes emerge depending on the physical obstacles such as buildings, trees or moving objects like trucks in the urban dense area (Musa et al. 2018). In the proposed scheme, unintentional NLOS nodes emerge as moving obstacles and physical objects are detected for achieving predominant reliable emergency message dissemination in the vehicular network. Moreover, mobile objects like trucks introduce interference during vehicular communication and can block the visibility of drivers and Line-Of-Sight (LOS) communication. These moving vehicles comprise of obstacles with different shapes, speeds, densities and compositions which can attribute towards additional NLOS situations (Gazzah et al. 2016). The obstacles can impact information updation among neighboring vehicles and communication of location information. The existence of obstacles prevents the sharing of information such as location, direction and speed associated with inter-vehicle communication. This prevention of potential information from obstacles results in fatal accidents that could occur on the road. In spite of suitable multi-hopping techniques used for transmitting a warning message beyond the range of communication, packet collisions, interference and hidden NLOS nodes unfortunately terminate the process of data dissemination in multi-hopping based broadcasting. The NLOS nodes need to be positioned with precise and rapid rate for dealing with delay minimization (Kaiwartya et al. 2018). A comprehensive protocol that reduces latency during emergency message delivery is essential in VANETs. Moreover, maximum coverage among the vehicular nodes need to be established and maintained for reducing the time delay between the generation and reception of warning messages (Luo et al. 2018). Thus, a reliable detection or positioning scheme needs to be developed and deployed in the vehicular network for identifying the NLOS nodes with the objective to sustain indispensable emergency data transmission in the network.

From the recent past, a significant number of researchers have contributed a quantifiable number of works in the literature for addressing the challenges that influences or causes NLOS situations. Most of the research works concentrate on the challenge of communication range, signal interference, signal blockage, authentication and signal strength. On the other hand, NLOS node detection and location verification approaches that determine the availability of the vehicular node, reliability of the message sender, position verification of nodes and various problems associated with integrity and Quality of Service (QoS) are also proposed. In particular, research schemes focusing on the accurate location verification of NLOS nodes are considered to be highly important in emergency situations. The NLOS node positioning scheme is classified into range-based and range-free detection techniques depending on the utilization of distance information and inherited principles of propagation model. These NLOS positioning schemes are implemented in the vehicular network either based on the use of anchor nodes or cooperative positioning process. Compared to the anchor node-based NLOS positioning scheme, cooperative positioning schemes is considered to be more successful since it exploits the merits of V2V communication. In cooperative positioning schemes, the neighboring nodes of the NLOS node share information associated with their locations and provide relative distance between them and their neighbors. Moreover, the contribution of weighted inertia-based dynamic virtual bat algorithm confirms the superiority of the meta-heuristic algorithms for efficient NLOS node positioning in vehicular networks (Amuthan and Kaviarasan 2019a, b). In addition, the Population-based meta-heuristic approach named Raccoon Optimization Algorithm (ROA) motivates its usage in the process of NLOS node localization (Koohi et al. 2018). ROA is used for NLOS localization because of its power and memory in searching the search space and remembering them for determining the global optimum solution with rapid time coverage and better accuracy similar to the weighted inertia-based dynamic virtual bat algorithm.

In this paper, Raccoon Optimization Algorithm-based Accurate Positioning Scheme (ROA-APS) is proposed for accurate positioning of NLOS nodes with improved accuracy to enhance the reliability in warning message delivery in vehicular networks. This ROA-APS reliably and rapidly positions the NLOS nodes based on the search phenomenon that mimic the rummaging behaviors of real raccoons foraging for food based on their sensitive and dexterous paws. It is proposed as a cooperative positioning scheme that inherits the potential of determining the solutions and remembering them for a time duration, such that the accurate positions of the NLOS nodes can be identified and updated based on the information derived from the neighboring nodes during mobility. It is proposed as a significant methodology that ensures maximized reliability and reduced latency in the event of warning message exchange by maintaining the tradeoff between the local and global search process. It incorporates maximum probability of acquiring higher adaptability through active learning in order to confirm optimal localization of NLOS nodes. It includes distance information for calculating position accuracy based on vehicle trajectory, distance information error and number of vehicles with the weighted average method for ascertaining maximum confidence in NLOS positioning. The simulation experiments of the proposed ROA-APS and the benchmarked scheme is conducted using EstiNet with the evaluation parameters of positioning accuracy, emergency message dissemination rate, positioning error, neighbor vehicles awareness rate and positioning time under the impact of different vehicle densities and NLOS nodes.

The major contributions of the proposed ROA-APS are listed below.

(i) It is proposed as a cooperative positioning scheme with the intelligent searching behavior of Raccoons that estimate the deviation between current solutions (current position of NLOS nodes) and the previous solution (previous position of NLOS nodes) for better localization efficiency.

(ii) It is proposed for increasing the search efficiency that concentrates on NLOS localization offering better active learning-based adaptability.

(iii) It is propounded as a significant NLOS positioning methodology that sustains the tradeoff between local and global searches independent of their location that lies between the hidden and tractable neighboring nodes.

(iv) It is proposed with Initial Visible Population (IVP) and preservation parameter for preventing the search process from being trapped into the local point of optimality in the exploitation phase.

The remaining sections of the paper are structured as follows. Section 2 presents the comprehensive review of the proposed NLOS node positioning schemes propounded in the literature over the recent years with their merits and shortcomings. Section 3 demonstrates the detailed view of the proposed ROA-APS with significant parameters contributing towards the process of efficient NLOS node positioning process. Section 4 exemplars the simulation setup and results of the proposed ROA-APS evaluated based on the evaluation metrics of positioning accuracy, emergency message dissemination rate, positioning error, neighbor vehicles awareness rate and positioning time under the impact of different vehicle density and NLOS nodes. Section 5 concludes the paper with major contributions and future scope of enhancement.

2 Related work

In this section, the comprehensive review of the existing NLOS node positioning approaches contributed in the recent years are presented with their pros and cons.

A decentralized cooperative vehicle positioning scheme based on Bayesian probability is proposed for permitting the vehicles to utilize the estimation of its GPS positions with respect to other vehicles that use GPS data for measuring inter-vehicle distances (Rohani et al. 2015). This Bayesian approach uses the tracking algorithms with the merits of Extended Kalman Filter (EKF) for pre-filtering the measurements of GPS positioning. This positioning schema is proposed for enhancing the GPS vehicle positions based on the estimated inter-vehicle distances determined with respect to different vehicular clusters. It inherits the benefits of the existing ego positioning algorithm that utilizes GPS for effective hidden NLOS node localization. It incorporates the strategy of distance measurements for minimizing the system cost without the requirement of new sensor range. It also provides the opportunity for incorporating the current communication equipments for estimating the distance in spite of various limitations inherent in them. It is applied for automotive and outdoor applications. However, the rate of localization and positioning accuracy of the Bayesian approach is identified to be comparatively low on par with the conventional approaches. Then, a cooperative localization approach using two state Markov chain is proposed for positioning NLOS and LOS node in the vehicular network (Li et al. 2016). This cooperative localization approach incorporates the time of arrival measurements for representing the switching characteristics between the NLOS and LOS situations. It is made adaptive as a state estimation strategy that includes a category of jump probabilities with multiple parameters of switching between Markov nonlinear properties. It is developed with the characteristics of multiple sensor and filter strategy that applies the collaboration of Extended Kalman Filter (EKF) and the interacting multiple model. It also uses the cooperative measurements of anchor nodes for sequential processing of distance data in centralized manner. This two state Markov chain model prevents the inadequacy involved in determining the actual positions of the mobile vehicular nodes. However, the estimation of distance needs to be achieved only through cooperative EKF that has the possibility of increasing communication overhead with increased localization error.

A Beacon Packet-based Cooperative Localization Approach (BPCLA) is proposed with the merits of the weighted least square method that predicts the position of the NLOS nodes (Fascista et al. 2016). It is developed by exploiting the properties of Vehicle-to-Infrastructure (V2I) for the opportunistic use of beacon packets in order to derive the Angle of Arrival (AoA) measurements. It is developed as a GPS-free positioning scheme attempted to derive benefits from the reliable measurement factors that are potentially collected from devices that are nearer to the Road Side Units (RSUs). However, this BPCLA includes a very high Signal-to-Noise Ratio (SNR) that results in precise angular resolution-with a high degree of robustness. But, it is identified to possess a number of limitations with the phenomena of multipath data communication. A Cooperative Volunteer Protocol-based NLOS Positioning Scheme (CVP-NPS) is proposed as a cooperative methodology that uses significant volunteer nodes (generally anchor nodes or reference nodes) to favor reliable warning data delivery (Alodadi et al. 2017). It is developed as a contextual sensitive approach that discriminates OBU components and their cooperation for reactive decision making under emergency NLOS situations. It is proposed as a significant improvement of GRANT protocols with an improved degree of channel utilization, neighborhood awareness, latency and packet delivery ratio. It is identified to exhibit a successful rate of NLOS node positioning in the urban areas intersection points and highway scenario. A fuzzy trust model-based NLOS positioning scheme is proposed with the merits of plausibility and experience to detect the existence of NLOS nodes (Soleymani et al. 2017). This trust-based NLOS node detection scheme executes a number of security checks that guarantees correctness of information received from trusted vehicles. It also adopts the use of fog nodes to estimate the accuracy level associated with the location of the emergency event. It is determined to detect faulty nodes and malicious attackers in order to prevent imprecision and uncertainty that are most possible in LOS and NLOS scenarios. It is formulated as a reliable approach that can handle the risk and uncertainties emerging from unreliable information shared in vehicular environments.

Time of Arrival (ToA) measurements-based improved subspace algorithm is proposed for NLOS node positioning with the view to enhance the degree of warning message delivery (Ansari et al. 2018). It is contributed as a solution of closed form which is resistive to noise that gets included during large measurements. It utilizes the aspect of dimensionality and scalar product in the form of the Eigen value. This trust-based NLOS model uses the advantages of Cramér-Rao Lower Bound (CRLB) for quantifying its significance independent of the position of hidden nodes with respect to its neighboring vehicular nodes. This improved subspace algorithm is confirmed to be more optimal than the traditional methods of localization, particularly when the number of anchors is few at the site of RSUs with a huge variance in noise. Then, a cooperative NLOS node positioning scheme called Dead Reckoning (DR) and a Geometric Dilution Of Precision (GDOP) based on Cooperative Positioning (CP) (DR-GDOP-CP) is developed with the significance of an inherited DR-based GDOP method for adding more accuracy in detection (Nascimento et al. 2018). This NLOS node precise positioning scheme leverages the significances of vehicular sensors that in turn include digital compasses, gyroscopes and odometers that help the vehicles to exchange their exact locations and information associated with their movements. This localization schema plays an anchor role in adjusting the final position of the vehicles based on a digital map that uses the dimensions of road geometry. It confirms average gains of approximately 97.12–98.21% and 83.62–88.82% on par with the traditional GPS solution. It also confirms a reduction in mean absolute Root Mean Square Error (RMSE) to a threshold level of 3–5 m. However, the positioning error is high and rate of positioning is improved to the maximum level. Dynamic Virtual Bat Aware Weighted Inertia-based NLOS localization (DVBAWI-NLS) scheme with weighted inertial factor is used for positioning the NLOS nodes for minimizing the delay incurred in the distribution of emergency information (Amuthan and Kaviarasan 2019a, b). It specifically utilizes the factor of weighted inertia for eliminating premature convergence that hinders the determination of accurate position associated with the hidden NLOS nodes. It includes an adaptive approach that aids in dynamically increasing and decreasing the search space depending on the predicted distance between a hidden node and its correspondingly closely located neighboring nodes. The results confirm a significant improvement in network latency, channel utilization and warning message delivery when compared to the range-free localization approaches. It is also identified as the predominant work that motivates the option of utilizing nature-inspired optimization algorithm contributed for positioning NLOS nodes in vehicular networks.

In addition, Distance Information-based improved cooperative vehicle positioning scheme called Cooperative Vehicle Localization Improvement using Distance information (CoVaLID) is proposed for determining the accurate positions of neighboring vehicles for disseminating warning messages with reduced errors (Lobo et al. 2019). This accurate positioning method also includes an EKF for executing data fusion process with possible extraction of distance information. This solution utilizes the distance information for estimating the location accuracy associated with the dimensions of errors in distance information, vehicle trajectory and number of vehicles. It uses a method of weighted average for enforcing more confidence over the distance information shared, when the hidden NLOS nodes are much closer to the reference nodes used for accurate positioning. The results of the DRSS-based positioning strategy confirm an error of 63% when compared to the state-of-the-art approaches used for NLOS localization processes. Differential Received Signal Strength-based Node Localization Scheme (DRSS-NLS) is proposed for preventing the problems associated with latency and reliability which are more common in most of the existing least square methods (Danaee and Behnia 2020). This significant improvement in DRSS method is initiated for including the constraint of non-linearity between the model parameters and utilizing them effectively. It is formulated with the mix of four DRSS-based positioning approaches that inherit different possibilities of weight and covariance matrices. Each of the DRSS-based positioning strategy includes a two stage process that estimates an initial coarse location step followed by the refined localization phase with non-linear dependency. The variants of the DRSS-based positioning strategies are selected and applied for positioning based on the factors of Signal-to-Noise (SNR) range.

In addition, Table 1 presents the summary of the reviewed existing techniques proposed in the literature with their merits and demerits that form the foundation for the formulation of the proposed ROA-APS.

Based on the limitations identified from Table 1, the proposed ROA-APS is proposed for preventing or handling them during the process of NLOS node localization in vehicular network.

3 Raccoon optimization algorithm-based accurate NLOS nodes positioning scheme (ROA-APS)

Raccoon Optimization Algorithm-based Accurate NLOS nodes Positioning Scheme (ROA-APS) is proposed as an effective approach that concentrates on the process of finding the location of NLOS nodes. This proposed ROA-APS determines the global point of optimality with the help of predefined functions that are derived based on the inspiration from the food searching characteristics of raccoons. In ROA-APS, the fitness function is considered by taking the vehicular network and the factors that contribute towards the localization of NLOS nodes in the network by making use of reference nodes. These reference nodes are considered to be deployed as search agents and the different feasible solutions (location of the NLOS nodes) identified in the network area of localization represent the candidate solutions. The core objective of this ROA-APS completely concentrates on the identification of NLOS nodes (best solution) from the possible set of solutions that could be determined in the network. This algorithm incorporates two populations that correspond to the reachable and visible zones. These sets of populations are explained in Sects. 3.2.2 and 3.2.3. The complete process of this proposed ROA-APS is partitioned into three steps including (i) Definition of parameters, (ii) Initialization of parameters and (iii) Core loop. The detailed view of each of the aforementioned phases is given below.

3.1 Definition of parameters

The various parameters that are used in the implementation of the proposed ROA-APS are explained as follows.

3.1.1 Radius of reachable zone (RRZ)

In contrast to the existing optimization algorithms, this proposed ROA-APS determines the candidate solutions (possible location of NLOS nodes) of the population to be within the reachable zone of the search agent. This ROA-APS thereby prevents the generation of candidate solution from anywhere inside the domain of problem solution. Thus, this algorithm utilizes a radius of this population of reachable zone which is always the minimum distance between the members of the population and current location of the search agent. This radius is termed as the RRZ and it is dynamically varied depending on the location of the reference nodes with respect to NLOS nodes.

Table 1 Summary of merits and demerits of the reviewed NLOS localization schemes

Authors	Mechanism	Merits	Demerits
Rohani et al. (2015)	Bayesian approach	Offers the benefits of the existing ego positioning algorithm that uses GPS for effective hidden NLOS node localization Minimizes the system cost by including a strategy of distance measurement	Offers decreased rate of localization and positioning accuracy on par with the conventional approaches
Li et al. (2016)	Cooperative localization approach using two state Markov chain	Adaptive as a state estimation strategy by including jump probabilities with multiple parameters of switching between Markov non-linear properties Overcomes inadequacy involved in determining the actual positions of mobile vehicular nodes	Involves increased communication with more localization error due to the use of cooperative EKF in distance estimation
Fascista et al. (2016)	Beacon Packet-based Cooperative Localization Approach (BPCLA)	Includes the merits of weighted least square method that predicts the positions of NLOS nodes Includes GPS-free positioning scheme to derive benefits from reliable measurement factors collected from devices nearer to the RSUs	Includes a very high SNR that results in precise angular resolution with a high degree of robustness
Alodadi et al. (2017)	Cooperative Volunteer Protocol-based NLOS Positioning Scheme (CVP-NPS)	Significant improvement of GRANT protocols with an improved degree of channel utilization, neighborhood awareness, latency and packet delivery ratio Identified to exhibit a successful rate of NLOS node positioning in the urban areas intersection points and highway scenario	The rate of localization error is considered to still possess a room for improvement
Soleymani et al. (2017)	Fuzzy trust model-based NLOS positioning scheme	Guarantees correctness of information received from trusted vehicles by executing a number of security checks Capable of detecting faulty nodes and malicious attackers in the prevention of imprecision and uncertainty that are possible in LOS and NLOS scenarios	Increases the time of localization and communication overhead with the number of security checks involved in detecting malicious vehicles
Ansari et al. (2018)	Time of Arrival (ToA) measurements-based improved subspace algorithm	Uses the advantages of Cramér-Rao Lower Bound (CRLB) for quantifying its significance independent of the position of hidden nodes in contrast to the neighbouring vehicular nodes Optimal than the traditional methods of localization, particularly when the number of anchors are few at the site of RSUs with a huge variance in noise	Involves increased number of anchor nodes and more communication overhead in the process of localization

Table 1 (continued)

Authors	Mechanism	Merits	Demerits
Nascimento et al. (2018)	Dead Reckoning (DR) and a Geometric Dilution Of Precision (GDOP) based on Cooperative Positioning (CP) (DR-GDOP-CP)	Leverages the significance of vehicular sensors that in turn includes digital compasses, gyroscopes and odometers that help the vehicles to exchange their exact locations and information associated with their movements Plays an anchor role in adjusting the final position of the vehicles based on a digital map that uses the dimensions of road geometry	Involves increased positioning error and reduced mean gains in RMSE during localization Offers decreased rate of positioning
Amuthan and Kaviarasan (2019b, a)	Dynamic Virtual Bat Aware Weighted Inertia-based NLOS Localization (DVBAWI-NLS)	Eliminates premature convergence that hinders the determination of accurate positions of hidden NLOS nodes by using the factor of weighted inertia Aids in dynamically increasing and decreasing the search space depending on the predicted distance between a hidden node and its corresponding closely located neighbouring nodes	Reduced network latency with enhanced channel utilization and warning message delivery under range-free localization exists is possible
Lobo et al. (2019)	Cooperative Vehicle Localization Improvement using Distance information (CoVaLID)	Determines accurate positions of neighbouring vehicles for disseminating warning messages with reduced errors Enforces more confidence over the shared distance information when the hidden NLOS nodes are much closer to the reference nodes for accurate positioning by using weighted average	Offers higher Mean absolute error and standard deviation in localization on par with the existing baseline schemes
Danaee and Behnia (2020)	Differential Received Signal Strength-based Node Localization Scheme (DRSS-NLS)	Overcomes the problems associated with latency and reliability which are more common in most of the existing least square methods Includes the constraint of non-linearity between the model parameters and utilizes them effectively	Offers reduced accuracy of localization not upto the acceptance level

3.1.2 Radius of visible zone (RVZ)

The visible zone corresponds to the area in which the search agents can verify the position of the NLOS nodes. This visible zone is highly restricted by the Radius of Visible Zone (RVZ). RVZ is the maximum distance between the members of the population and current location of the search agent.

3.1.3 Cardinality of reachable zone

Cardinality of reachable zone defines the number of candidate solutions that are well situated within the population of reachable zone. The number of candidate solutions that lies inside PRZ is termed 'NRZ' and completely depends on the number of reference nodes required for the localization process.

3.1.4 Cardinality of visible zone

Cardinality of visible zone defines the number of candidate solutions that are well situated inside the population of visible zone. The number of candidate solutions that lies inside PVZ is termed 'NVZ' and completely depends on the number of reference nodes required for the localization process. However, the cardinality of visible zone is always less than the cardinality of reachable zone (NVZ < NRZ).

3.1.5 Migration factor (MF)

Most of the optimization algorithms are identified to be entangled in the local point of optimality during its execution process. This results in a sub-optimal solution in the problem domain, even though better optimal solution may exist in the other regions of the solution domain. This local point of optimality deceives the algorithm leading to a non-global solution. This proposed ROA-APS has the potential of simultaneously searching the population of reachable and visible zones. This process of searching greatly minimizes the risk of being stuck in the optimal point of local search. It is also considered to enhance the ability of global exploration associated with the algorithm. However, falling into the local point of optimality may still happen during the process of localizing NLOS nodes. Hence, the proposed ROA-APS uses the migration in order to prevent trapping of local optimum. The process of migration is required when the location of search agents does not change for a predefined count of iterations. This migration is a reliable attempt towards preservation. Migration Factor (MF) is referred to the number of predefined iterations in which the possibility of preservations is achieved.

3.1.6 Number of iterations

This proposed ROA-APS is also considered to be iterative in nature similar to the most common cases of the optimization algorithms. The execution of the algorithm is repeated specified number of times. In this algorithm, the number of iterations is denoted by '$\mathrm{Max}_{\mathrm{Iter}}$'. For better understanding, Table 2 presents the nomenclature of notations and their description used in the proposed ROA-APS.

3.2 Initialization of parameters

The initialization step of the proposed ROA-APS is commenced by setting the algorithmic parameters. This process of initialization in the proposed ROA-APS comprises of three steps such as (i) Initial location of raccoon (search agent), (ii) Construction of initial reachable population and (iii) Building the visible population. Each step of parameter initialization is explained below.

3.2.1 Initial location of raccoon (search agent)

In the initialization process of locating the raccoon (search agent), a random function is used for assigning a random action to the raccoon (search agent) in the domain associated with the solution of the problem. In this algorithmic process, the possible location of the search agents corresponding to iteration 'i' is represented as $\mathrm{R}_{\mathrm{CL(i)}}\left(0 \leq \mathrm{i} \leq \mathrm{Max}_{\mathrm{Iter}}\right)$. This step of initialization is considered as the zeroth iteration, hence the initial location of the search agent is considered as '$\mathrm{R}_{\mathrm{CL(0)}}$'. The raccoon inspired search agents are known for their very good memory potentiality. It is capable of remembering the superior food location in localizing NLOS nodes in the entire search process. This remembered superior food locations are denoted as '$\mathrm{OPT}_{\mathrm{G}}$'. This step of initialization is considered as iteration zero, since the location of the search agents are not evaluated. This parameter '$\mathrm{OPT}_{\mathrm{G}}$' is initialized with the current random location of the search agent highlighted in Eq. (1).

$$\mathrm{OPT}_{\mathrm{G}} = \mathrm{R}_{\mathrm{CL(SA)}} \tag{1}$$

3.2.2 Construction of initial reachable population

In this step, the reachable population is constructed around the current location of the search agent '$\mathrm{R}_{\mathrm{CL(0)}}$', once it is initialized. The first population in the ROA-APS is termed as the Population of Reachable Zone (PRZ). This PRZ represents the circle around the search agent with the radius corresponding to its radius termed Radius of Reachable Zone (RRZ). This PRZ also includes the complete collection of all feasible solutions.

Table 2 Nomenclature of notations and their description used in the ROA-APS scheme

Notation	Description
$R_{CL(i)}$	Possible location of the search agents corresponding to iteration 'i'
OPT_G	Remembered superior food locations
PRZ	Population of Reachable Zone
PVZ	Population of Visible Zone
RVZ	Radius of Visible Zone
RRZ	Radius of Reachable Zone
NRZ	Number of candidate solutions (position of NLOS nodes) in the Reachable Zone
NVZ	Number of candidate solutions (position of NLOS nodes) in the Visible Zone
MF	Migration Factor
$PRZ_{(SA)}$	Population of Reachable Zone of the SA
$PRZ_{(0)}$	Initial Population of Reachable Zone
$PVZ_{(0)}$	Initial Population of Visible Zone
$R_{BEST(0)}$, $R_{BEST(i-1)}$	Best reachable candidate solution in the Reachable Zone
$S_{BEST(0)}$, $S_{BEST(i-1)}$	Best reachable candidate solution in the Visible Zone
$r_{SC(0)}, r_{SC(1)}, \dots \dots r_{SC(NRZ)}$	Random candidate solutions in the Reachable Zone
$r_{SC(i)}$	Randomly selected candidates representing the current locations of NLOS nodes before localization
$x_0, x_1 \dots \dots, x_{NRZ}$	Randomly selected candidates of NLOS nodes
$\alpha(c_{loc}, r_{SC})$	Distance between the current location of search agent and the candidate solution
$u_{SC(0)}, u_{SC(1)}, \dots ..u_{SC(RVZ)}$	Random candidate solutions in the Visible Zone
$u_{SC(i)}$	Randomly selected candidates lying between RRZ and RVZ representing the current location of the NLOS nodes before localization
$y_0, y_1, \dots \dots y_{NVZ}$	Candidate solutions lying above RRZ and below RVZ
$\alpha\left(c_{loc}(PVZ), u_{SC(i)}\right)$	Distance between the current location of search agent and the candidate solution determined in the PVZ area
$S_{BEST(0)}$	Superior candidate solution on the PVZ area
$u_{(j)}$	Maximizing utility function
Pr_n	Preserving parameter
Max_{Iter}	Maximum number of iterations
$c_{loc(i-1)}$, $c_{loc(i)}$	Previous and current locations of the search agent
f(g)	Superior fitness value identified in the previous iteration, Reachable Zone and Visible Zone
$f\left(c_1\right)$	Fitness function that determines maximum among the superior fitness values identified in the previous iteration, Reachable Zone and Visible Zone
$Fitness_{Fn}$	Fitness function
w_1, w_2	Weights for fitness calculation
$Fn_{(1)}$	Possible predicted distance between the reference node and the unknown NLOS nodes
$Fn_{(2)}$	Distance of the unknown nodes from the obstacles that introduce NLOS conditions

In specific, this population of PRZ highlights the collection of feasible NLOS nodes that could be localized by the Search Agent (SA) with its capability of visualization and memory. However, the set of all feasible solutions in a particular area of localization might be enormous. Hence, only a specific subset of random candidate solutions is considered for investigation as specified in Eq. (2):

$$PRZ_{(SA)} = \left\{r_{SC(0)}, r_{SC(1)}, \dots \dots r_{SC(NRZ)}\right\} \tag{2}$$

where 'NRZ' is the number of candidates in the Reachable Zone of the search agent. This 'NRZ' is determined based on the number of reference nodes required for localizing the NLOS nodes in the network. Further, $r_{SC(i)}, 0 \leq i \leq NRZ$ refers to the randomly selected candidates that represent the current locations of the NLOS nodes before localization process. Furthermore, the determination of '$r_{SC(i)}$' is considered as the N-dimensional optimization problem as highlighted in Eq. (3).

$$r_{SC(i)} = \left(x_0,\ x_1 \dots \dots,\ x_{NRZ}\right), \text{ where } 0 \leq i \leq NRZ. \tag{3}$$

In this context, if the distance between the current location of search agent and the candidate solution is $\alpha\left(c_{loc},\ r_{SC}\right)$, then the candidates existing inside PRZ need to satisfy the relation specified in Eq. (4).

$$0 < \alpha\left(c_{loc},\ r_{SC}\right) \le \text{PRZ},\ \text{where } 0 \le i \le \text{NRZ}. \tag{4}$$

At this juncture, PRZ is considered to be the important parameter which is helpful in examining the complete set of feasible solutions more precisely. In this context, precision pertains to the large number of candidate solutions that could be investigated by the search agent for localizing the NLOS nodes. Thus, PRZ is initially represented as 'PRZ_0' which is defined based on Eq. (5).

$$PRZ_0 = r_{SC(i)} \middle| \ i \in \{0, 1, \ldots.. \text{NRZ}\} \text{ and } 0 < \alpha\left(c_{loc}, r_{SC}\right) \le \text{PRZ} \tag{5}$$

This ROA-APS based localization process thoroughly searches for the best solution '$R_{BEST(0)}$' among the collection of the candidate solutions considered for examination, once the initial reachable population is constructed. This '$R_{BEST(0)}$' is determined based on the maximization problem and fitness function used for optimization as depicted in Eq. (6).

$$\begin{gathered} R_{BEST(0)} = r_{(j)},\ \text{where } r_{(j)} \in PRZ_0 \text{ and} \\ f\left(r_{(j)}\right) = \text{Max}\left\{ f\left(r_{(i)}\right) \middle| \ r_{(i)} \in PRZ_0 \right\},\ \text{where } 0 \le i \le \text{NRZ}. \end{gathered} \tag{6}$$

3.2.3 Building the visible population

In this step, the visible population with respect to the search agents is built after the construction of the reachable population attained in the previous step. Similar to PRZ, the proposed ROA-APS uses the second population named Population of Visible Zone (PVZ). This PVZ depicts the circle around the Radius of Visible Zone (RVZ) with the location of the search agent at the center. In particular, this population of PVZ represents the collection of feasible NLOS nodes that could be localized by the search agent with its visualization potential even when it is beyond RRZ. This population consists of a number of visible and feasible solutions that lies between RRZ and RVZ as represented in Eq. (7):

$$\text{PVZ} = \left\{u_{SC(0)}, u_{SC(1)}, \ldots .. u_{SC(RVZ)}\right\} \tag{7}$$

where 'PVZ' is the number of candidates that lies beyond RRZ and below RVZ in the reachable zone of the search agent. The value of PVZ is determined based on the number of reference nodes required for localizing the NLOS nodes in the network that lies in between RRZ and RVZ. In this context, $u_{SC(i)}(0 \le i \le \text{NRZ})$ refers to the randomly selected candidates (lying between RRZ and RVZ) that represent the current location of the NLOS nodes before localization. Furthermore, the determination of '$u_{SC(i)}$' is considered as the N-dimensional optimization problem as highlighted in Eq. (8).

$$u_{SC(i)} = \left(y_0,\ y_1,\ \ldots \ldots y_{NVZ}\right),\ \text{where } 0 \le i \le \text{NVZ}. \tag{8}$$

Furthermore, the determined potential candidate solutions (location of NLOS nodes) need to exist inside the reachable zone of the search agent. In practical, RVZ and RRZ are the possible regions of search agents' exploration. However, RVZ is always greater than RRZ for estimating and exploiting the second population. In other words, the distance between the individual NLOS nodes of this PVZ and the search agent location need to be greater than RRZ and less than or equal to the RVZ. If the distance between the current location of search agent and the candidate solution determined in the PVZ area is $\alpha\left(c_{loc}\ (\text{PVZ}),\ u_{SC(i)}\right)$, then the candidates existing inside PVZ need to satisfy the relation specified in Eq. (9).

$$\text{PRZ} < \alpha\left(c_{loc}\ (\text{PVZ}),\ r_{SC(i)}\right) \le \text{PVZ},\ \text{where } 0 \le i \le \text{NVZ}. \tag{9}$$

Similar to PRZ, PVZ is also identified as the significant parameter useful for exploiting the comprehensive collection of candidate solutions accurately. Hence, the initial Population of Visible Zone '$PVZ_{(0)}$' is initially depicted based on Eq. (10).

$$\begin{aligned} PVZ_{(0)} = \Big\{ u_{SC(i)} \Big| i \in \{0, 1,\ \ldots..,\ \text{NVZ}\} \text{ and PRZ} \\ < \alpha\left(c_{loc}\ (\text{PVZ}),\ r_{SC(i)}\right) \le \text{PVZ} \Big\} \end{aligned} \tag{10}$$

In addition, the superior member of the zone is identified after the construction of PVZ as analogous to the step of PRZ. This superior candidate solution on the PVZ area is labeled as '$S_{BEST(0)}$'. This '$S_{BEST(0)}$' is determined based on the maximization problem and fitness function used for optimization as depicted in Eq. (11).

$$\begin{gathered} S_{BEST(0)} = u_{(j)},\ \text{where } u_{(j)} \in PVZ_{(0)} \text{ and} \\ f\left(u_{(j)}\right) = \text{Max}\left\{ f\left(u_{(i)}\right) \middle| r_i \in PVZ_{(0)} \right\},\ \text{where } 0 \le i \le \text{NVZ}. \end{gathered} \tag{11}$$

3.2.4 Initialization of preserving parameter

In this initialization phase, a preservation value is defined based on the parameter of 'Pr_n'. This value of 'Pr_n' is used for evaluating the preservation degree. It is used for preventing the local optima which is detailed in the core loop section. In this step, the parameter 'Pr_n' is initialized to zero as presented in Eq. (12).

$$Pr_n = 0. \tag{12}$$

3.3 The CORE LOOP

The third part of the proposed ROA-APS repeats the steps such as (i) Relocation of the best location, (ii) Migration and (iii) Generating the next generation for 'Max_{Iter}' number of times.

3.3.1 Relocation to best location

In every iteration $i(0 \le i \le Max_{Iter})$, the superior value in the PRZ ($R_{BEST(i-1)}$), visible zone ($S_{BEST(i-1)}$) and the current location of the search agent '$c_{loc(i-1)}$' pertaining to the previous iteration are selected. Further, the search agent transits to the best location chosen from the predetermined values. As a consequence, the location of the search agent will be one among the location of the three values. Thus, the location of the search agent based on the fitness function can be defined based on the problem of maximizing optimization through Eq. (13).

$$c_{loc(i)} = c_l,\ \text{where}\ c_l \in \left\{c_{loc(i-1)}, R_{BEST(i-1)},\ S_{BEST(i-1)}\right\}\ \text{and}$$
$$f\left(c_l\right) = Max\left\{ f(g) | g \in \left\{c_{loc(i-1)}, R_{BEST(i-1)},\ S_{BEST(i-1)}\right\}\right\}. \tag{13}$$

3.3.2 Migration

The search agent is considered to reach the best solution in the local area of exploitation, if the location has not changed over a number of iterations even after imposing the process of relocation. However, the local optimal solution may be the best solution which could block proper execution of the algorithm. This condition is termed as preservation. In addressing the issue of preservation, the parameter 'Pr_n' is already defined in the initialized step and set to zero with an objective of evaluating the degree of preservation. If the location of the search agent with respect to the NLOS nodes does not relocate ($c_{loc(i)} = c_{loc(i-1)}$) in each core loop iteration, then the 'Pr_n' value is incremented by one ($Pr_n = Pr_n + 1$). On the other hand, if the location of the search agent with respect to the NLOS nodes is relocated ($c_{loc(i)} \ne c_{loc(i-1)}$) in each core loop iteration, then the 'Pr_n' value is reset to zero ($Pr_n = 0$).

$$Pr_b = (c_{loc(i)} = c_{loc(i-1)}) \rightarrow \left(Pr_n + 1\right) \bigwedge c_{loc(i)} \ne c_{loc(i-1)} \rightarrow 0 \tag{14}$$

At this juncture, the degree of preservation with respect to each iteration is verified by comparing the value of the Migration Factor (MF) with the value of preservation in order to prevent the algorithm from being stuck at the local point of optimality. When the condition $MF = Pr_n$ is identified, then the process of migration is performed. The process of migration refers to the process of relocating the search agent to a new location randomly outside the zone of visibility. The migration process is initiated for determining the best solution. This randomly selected location of the search agent can be any specific location which lies completely inside the domain of the problem by satisfying the condition specified in Eq. (15).

$$\alpha\left(c_{loc(i)}, c_{loc(i-1)}\right) > RVZ \tag{15}$$

The preservation parameter 'Pr_n' is again reset to zero, once the process of migration is performed. It is identified that the search agent is capable of remembering the best solution that has ever been identified as 'OPT_G'. Hence, the movement of the search agent will never influence the overall execution of the problem even if the migration process transits them to a location with worse solutions. However, the migration of the search agents happens gradually to the best places depending on the location of the NLOS nodes hidden in the network.

3.3.3 Producing the next generation

In this step, new populations which are similar to the initial population is generated at the end of each generation. The core difference visualized is the change in the location of the search again. The candidate solutions of the newly generated population will possess locations which is completely different from the location of the preceding population. This condition is checked when the search agent is present in the preservation position (previous position).

$$\begin{array}{c}\left(c_{loc(i)} = c_{loc(i-1)}\right) \iff (PRZ_{(i)} \cap PRZ_{(i-1)}) = \phi \\ \bigwedge \\ \left(c_{loc(i)} = c_{loc(i-1)}\right) \iff (PVZ_{(i)} \cap PVZ_{(i-1)}) = \phi\end{array} \tag{16}$$

Finally, the best fitness value of 'OPT_G' and '$c_{loc(i)}$' are determined after the core loop execution for 'Max_{Iter}' times as the best solution (position of NLOS nodes) localized during the entire process of searching process through reference nodes.

In this proposed ROA-APS, the fitness calculation of each raccoon search agent is considered as a multi-objective fitness function as presented in Eq. (17):

$$Fitness_{Fn} = w_1 \times Fn_{(1)} + w_2 \times Fn_{(2)} \tag{17}$$

where 'w_1' and 'w_2' are set to 0.5 in order to provide equal weights to the functions during localization. In the ROA function, '$Fn_{(1)}$' and '$Fn_{(2)}$' correspond to the possible predicted distance between the reference node and the unknown NLOS nodes and the distance of the unknown nodes from the obstacles that introduce NLOS conditions respectively.

In addition, the pseudocode of the proposed ROA-APS technique is presented as follows.

Algorithm: ROA-APS
Step 1: Definition of parameters
RRZ ← Radius of Reachable Zone
RVZ ← Radius of Visible Zone
NRZ ← Number of candidate solutions (position of NLOS nodes) in the reachable zone
NVZ ← Number of candidate solutions (position of NLOS nodes) in the visible zone
MF ← Migration Factor
$\mathrm{Max}_{\mathrm{Iter}}$ ← Maximum number of Iterations
Step 2: Initialization of the parameters
$\mathrm{PRZ}_{(0)}$← Initial Population of reachable zone
$\mathrm{PVZ}_{(0)}$← Initial Population of visible zone
$\mathrm{R}_{\mathrm{BEST}(0)}$← Best reachable candidate solution in the reachable zone
$\mathrm{S}_{\mathrm{BEST}(0)}$ ← Best reachable candidate solution in the visible zone
$\mathrm{Pr}_{\mathrm{n}} \leftarrow 0$
$\mathrm{OPT}_{\mathrm{G}} \leftarrow \mathrm{c}_{\mathrm{loc}(0)}$
$\mathrm{c}_{\mathrm{loc}(0)}$ ← The initial location of the candidate chosen randomly
Step 3: The core loop
for i=1 to $\mathrm{Max}_{\mathrm{Iter}}$ do
$\mathrm{c}_{\mathrm{loc}(\mathrm{i})}$ ← best location in $\mathrm{c}_{\mathrm{loc}(\mathrm{i}-1)}$, $\mathrm{R}_{\mathrm{BEST}(\mathrm{i}-1)}$and $\mathrm{S}_{\mathrm{BEST}(\mathrm{i}-1)}$
If ($\mathrm{f}(\mathrm{c}_{\mathrm{loc}(\mathrm{i})}) > \mathrm{f}(\mathrm{OPT}_{\mathrm{G}})$) then
$\mathrm{OPT}_{\mathrm{G}} \leftarrow \mathrm{c}_{\mathrm{loc}(\mathrm{i})}$
End if
If ($\mathrm{c}_{\mathrm{loc}(\mathrm{i})} = \mathrm{c}_{\mathrm{loc}(\mathrm{i}-1)}$) then (Preservation of search agents' solution)
$\mathrm{Pr}_{\mathrm{n}} = \mathrm{Pr}_{\mathrm{n}} + 1$
Else
$\mathrm{Pr}_{\mathrm{n}} = 0$
End if
If (Pr_{n} = MF) then (Process of Migration)
$\mathrm{c}_{\mathrm{loc}(\mathrm{i})}$← new random location that lies outside the region of $\mathrm{PVZ}_{(\mathrm{i}-1)}$
$\mathrm{Pr}_{\mathrm{n}} \leftarrow 0$
End if
$\mathrm{PRZ}_{(\mathrm{i})}$← Population of reachable zone at i^{th}iteration
$\mathrm{PVZ}_{(\mathrm{i})}$← Population of visible zone at i^{th}iteration
$\mathrm{R}_{\mathrm{BEST}(0)}$← Best candidate in the population of reachable zone
$\mathrm{S}_{\mathrm{BEST}(0)}$← Best candidate in the population of visible zone
End for
Step 4: Localization of NLOS nodes by search agent
If ($\mathrm{c}_{\mathrm{loc}(\mathrm{i})} = \mathrm{c}_{\mathrm{loc}(\mathrm{i}-1)}$) then
Return $\mathrm{c}_{\mathrm{loc}(\mathrm{i})}$ (location of NLOS nodes)
else
Return $\mathrm{OPT}_{\mathrm{G}}$ (Possible locations of vehicular nodes that could be localized)
End if

4 Simulation results and discussion

The localization potential of the proposed ROA-APS technique is explored and compared with the baseline NLOS localization schemes such as Dynamic Virtual Bat Aware Weighted Inertia-based NLOS localization (DVBAWI-NLS), Differential Received Signal Strength-based Node Localization Scheme (DRSS-NLS), Cooperative Volunteer Protocol-based NLOS Positioning Scheme (CVP-NPS) and Beacon Packet-based Cooperative Localization Approach (BPCLA) using the EstiNet network simulator. The simulation experiments of the proposed ROA-APS with the baseline approaches are conducted with 10 runs and the average of the runs of the proposed and benchmarked schemes are considered. MATLAB tool is used for drawing graphs of the results determined during the simulation experiments of the proposed ROA-APS technique and the benchmarked schemes.

The EstiNet Simulator is mainly utilized as it is potent in enabling the destination-based real vehicular movement and the existing IEEE 802.11p/1609 VANET network simulation which is highly feasible in the road lanes of VANET (Wang et al. 2013; Wang 2014; Urquiza-Aguiar et al. 2015; Janakiraman 2020). This EstiNet simulator originated from NCTUns which is widely used for conducting network associated research activities. It was established as a commercial software in the year 2011 and was renamed as EstiNet. The network simulation environment of EstiNet comprises of application layer, transport layer, network layer, control layer, media access control layer and physical layer. EstiNet is considered to facilitate higher user friendly Graphical User Interface (GUI) for enabling the user in constructing the simulated network more conveniently and providing visual display for observing and debugging simulation results. EstiNet supports simulation of VANETs and integrates the protocol stacks of Linux kernels. The Linux kernels related to the UDP/IP and TCP/IP protocol stacks are combined together in the simulated network for facilitating layer-3 and layer-4 protocol characteristics of network applications. The EstiNet simulator has the capability of transiting itself from the mode of simulation to emulation. It also provides the option to the simulated network or device to transmit or receive packets to or from other devices during its transition into the mode of emulation. This simulation framework aids the VANETs to add on and enable potential communication in the V2V and V2I communication in high speed scenarios. It has the capability of providing important traces and supporting customized maps for generating mobility. It also provides the support of defining the parameters or patterns for defining traffic signals, overtaking, lane changing, trip type, etc., It attains fast data transmission by supporting IEEE 802.11p. This simulator possesses built-in mobility generator, microscopic traffic model with the characteristics of multiple traffic flow models, traffic light, car following and speed models. Thus, EstiNet is considered to be advantageous over veins, NS2, NS3 and Omnet++ simulators.

This simulation experiment of the proposed ROA-APS Technique is conducted using the Open Street Map (OSM) (presented in Fig. 1) which is imported into the network simulator of EstiNet 8.1 for vehicle localization problem.

In addition, the simulation parameters and their associated values used for the deployment of ROA-APS technique are listed in Table 3. The environmental setup parameters and their associated values utilized in the proposed ROA-APS technique are completely selected based on inspiration and experience gained from reviewing most of the NLOS localization techniques proposed in the literature in the recent years (Malar et al. 2020a, b). Some of the specific state-of-the-art approaches inspired and utilized for assigning the parametric values are Cooperative Volunteer Protocol to detect NLOS nodes (Alodadi et al. 2017), An improved Rank Criterion-based NLOS node detection mechanism (Janakiraman, 2020) and Weighted Inertia-based Dynamic Virtual Bat Algorithm to detect NLOS nodes for reliable data dissemination (Amuthan and Kaviarasan 2019a, b). Moreover, Raccoon Optimization Algorithm (Koohi et al. 2018) is used for assigning the values to the parameters such as Radius of Visible Zone (RVZ), Radius of Reachable Zone (RRZ), Number of candidates in Reachable Zone (NRZ) and Number of candidates in Visible Zone (NVZ).

In the first part of the investigation, the significance of the proposed ROA-APS and the baseline DVBAWI-NLS, CVP-NPS and DRSS-NLS and BPCLA approaches are compared based on delivery rate of warning messages, rate of awareness to an emergency event, end-to-end delay and localization error for different neighborhood vehicular densities. Figures 2 and 3 highlight the plots of the proposed ROA-APS and the benchmarked DVBAWI-NLS, CVP-NPS, DRSS-NLS and BPCLA approaches investigated based on delivery rate of warning messages and rate of awareness to an emergency event for different neighborhood vehicular densities. The delivery rate of warning messages ascertained by the proposed ROA-APS scheme tends to decrease with an increase in the densities of the vehicular nodes. However, ROA-APS is identified to sustain the rate of warning message delivery mainly due to the utilization of PRZ and PVZ that play a key role in balancing the degree of exploitation and exploration. Thus, the emergency message dissemination rate of the proposed ROA-APS is confirmed to be enhanced by 11.42%, 13.94%, 15.75% and 17.54% superior to the baseline DVBAWI-NLS, CVP-NPS and DRSS-NLS and BPCLA approaches. The rate of awareness to an emergency event ensured by the proposed ROA-APS is observed to be maintained independent of the quantifiable increase in the number of vehicular nodes in the network. The maintenance in rate of awareness to an emergency event is attained by the proposed ROA-APS as it includes the benefits of

Fig. 1 OSM considered for simulation of the proposed ROA-APS technique

Table 3 Simulation setup parameters of the proposed ROA-APS technique

Parameter used for Simulation	Values
Area of simulation	1500 m × 15,000 m
Time of simulation	350 s
Range of transmission	200 m
Mobility generator type	OpenStreetMap
Maximum vehicles' speed	50 km/h and 70 km/h
Size of warning messages	512 bytes
Type of traffic	Constant bit rate (CBR)
Type of MAC protocol	IEEE 802.11p
Maximum number of vehicles	500
Fading model	Rician model
Migration Factor (MF)	3
Number of iterations	30
Radius of Visible Zone (RVZ)	3
Radius of Reachable Zone (RRZ)	1
Number of candidates in Reachable Zone (NRZ)	10
Number of candidates in Visible Zone (NVZ)	5

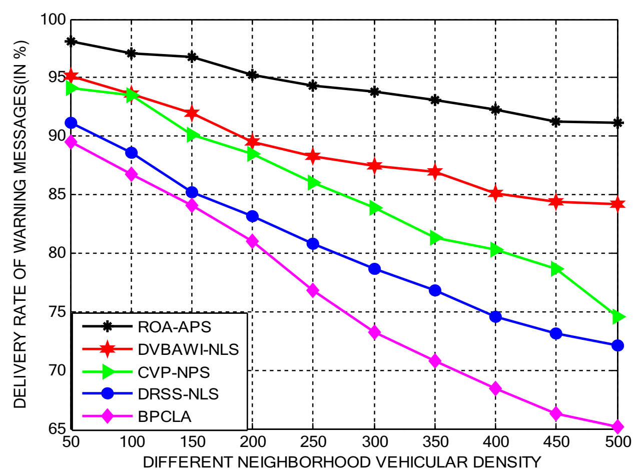

Fig. 2 Delivery rate of warning messages of the proposed ROA-APS scheme for varying neighborhood vehicular densities

preservation and migration factor to prevent the limitations of local and global searches utilized in the process of NLOS nodes' localization. Thus, the rate of awareness to an emergency event facilitated by the proposed ROA-APS is confirmed to be enhanced by 12.82%, 14.58%, 15.72% and

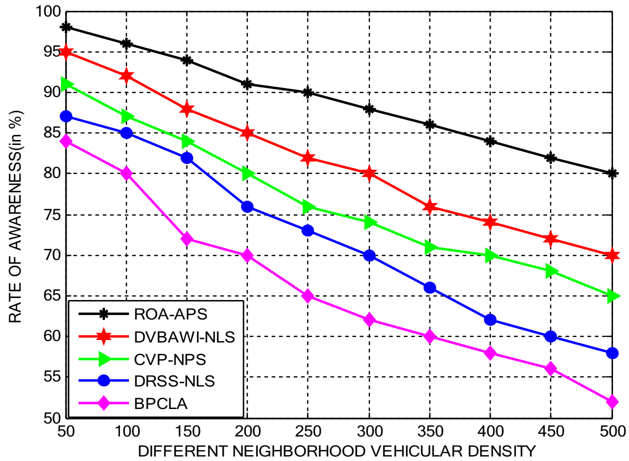

Fig. 3 Rate of awareness to emergency event of the proposed ROA-APS scheme for varying neighborhood vehicular densities

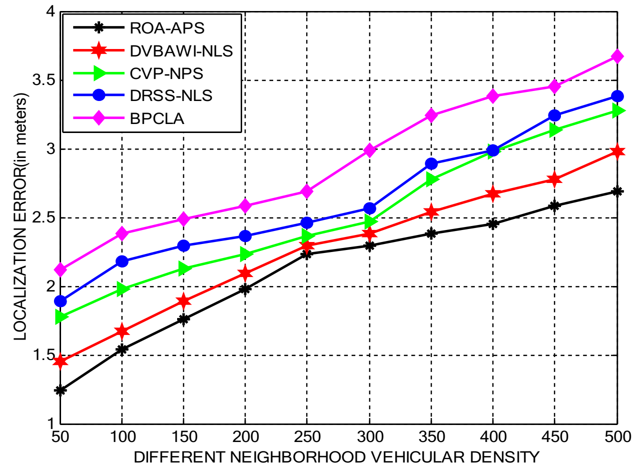

Fig. 5 Localization error of the proposed ROA-APS scheme for varying neighborhood vehicular densities

16.94% superior to the baseline DVBAWI-NLS, CVP-NPS and DRSS-NLS and BPCLA approaches.

Figures 4 and 5 demonstrate the end-to-end delay and localization error achieved by the proposed ROA-APS and the benchmarked DVBAWI-NLS, CVP-NPS, DRSS-NLS and BPCLA approaches for varying number of neighborhood vehicular densities. The end-to-end delay achieved by the proposed ROA-APS is considerably reduced, since the migration factor acts as the transition parameter for inducing rapid localization process. Likewise, the localization error is also predominantly minimized by the proposed ROA-APS since it localizes the hidden NLOS nodes independent of its position relative to the reference nodes. The end-to-end delay of the proposed ROA-APS is identified to be reduced by 12.84%, 14.92%, 16.28% and 18.21% when compared to the baseline DVBAWI-NLS, CVP-NPS and DRSS-NLS and BPCLA approaches. The localization error of the proposed

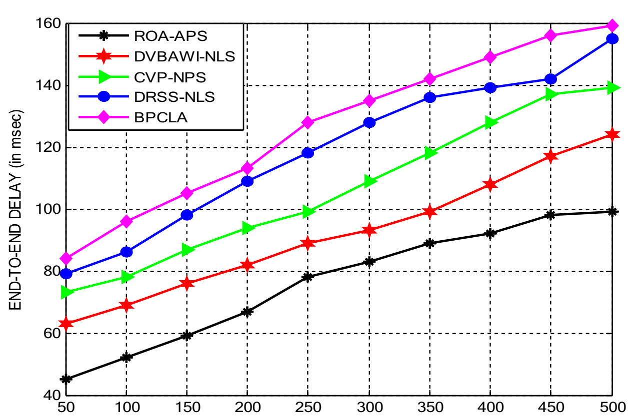

Fig. 4 End-to-end delay of the proposed ROA-APS scheme for varying neighborhood vehicular densities

ROA-APS is observed to be maintained, independent of the quantifiable increase in the number of vehicular nodes in the network. The localization error of the proposed ROA-APS is confirmed to be enhanced by 12.82%, 14.58%, 15.72% and 16.94% in contrast to the baseline DVBAWI-NLS, CVP-NPS and DRSS-NLS and BPCLA approaches.

In the second part of the investigation, the significance of the proposed ROA-APS and the baseline DVBAWI-NLS, CVP-NPS and DRSS-NLS and BPCLA approaches are compared based on delivery rate of warning messages, rate of awareness to an emergency event, end-to-end delay and localization error for varying number of NLOS nodes in the network. Figures 6 and 7 depict the delivery rate of warning messages and rate of awareness to an emergency event for different NLOS nodes in the network. The delivery rate of warning messages confirmed by the proposed ROA-APS is determined to decrease with an increase in the number of NLOS nodes. But, ROA-APS is estimated to uphold the rate of warning message delivered through the inclusion of RRZ and RVZ that exploits and explores the search space more precisely. The emergency message dissemination rate of the proposed ROA-APS for varying number of NLOS nodes is visualized to be improved by 9.74%, 11.21%, 13.86% and 15.82% in contrast to the baseline DVBAWI-NLS, CVP-NPS and DRSS-NLS and BPCLA approaches. The rate of awareness to an emergency event ensured by the proposed ROA-APS with different NLOS nodes is observed to be improved due to the maximized usage of different zones that helps in hidden node positioning. The rate of awareness to an emergency event facilitated by the proposed ROA-APS for varying number of NLOS nodes is confirmed to be enhanced by 10.64%, 14.58%, 15.72% and 16.94% when compard to the baseline DVBAWI-NLS, CVP-NPS, DRSS-NLS and BPCLA approaches.

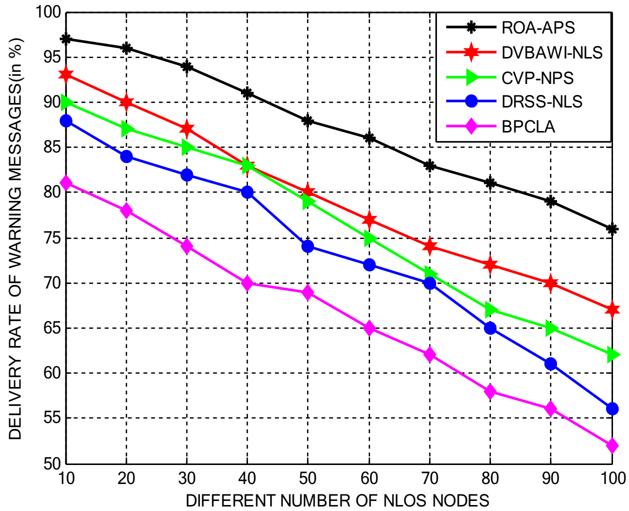

Fig. 6 Delivery rate of warning messages of the proposed ROA-APS scheme for varying number of NLOS nodes

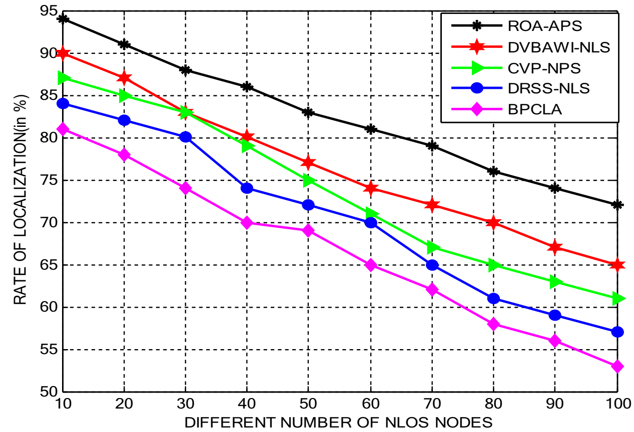

Fig. 8 Rate of localization of the proposed ROA-APS for varying number of NLOS nodes

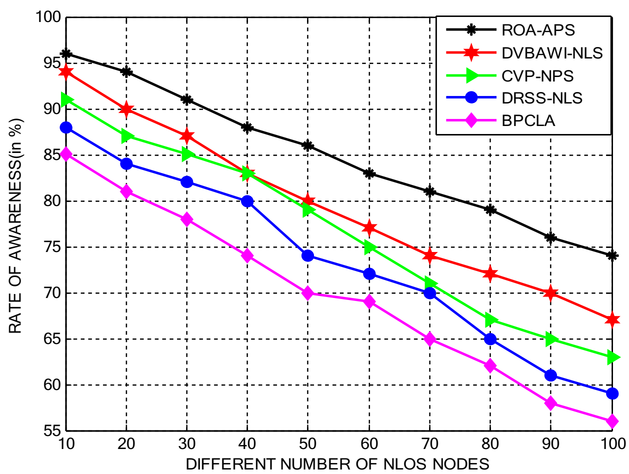

Fig. 7 Rate of awareness of the proposed ROA-APS scheme for varying number of NLOS nodes

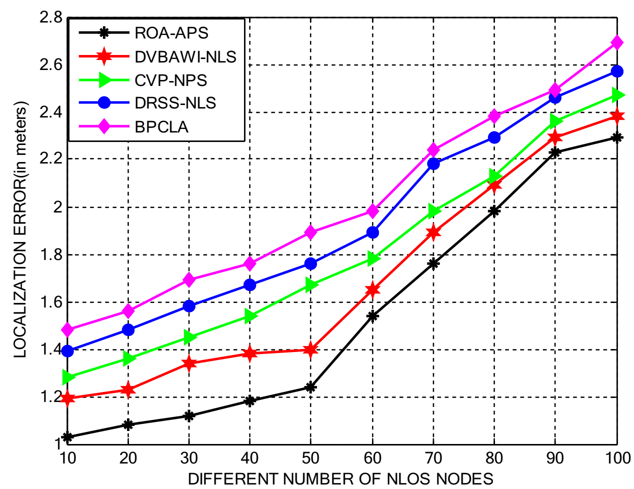

Fig. 9 Localization error of the proposed ROA-APS for varying number of NLOS nodes

Figures 8 and 9 highlight the rate of localization and localization error of the proposed ROA-APS and the baseline DVBAWI-NLS, CVP-NPS, DRSS-NLS and BPCLA approaches for varying number of NLOS nodes in the network. The rate of localization facilitated by the proposed ROA-APS is considerably significant, since it uses a minimum number of reference nodes for estimating the location of the NLOS nodes with a high degree of accuracy. Similarly, the localization error during the implementation of the proposed ROA-APS is also proved to be significantly reduced due to the utilization of different zones that aids in evaluating the candidate solutions for maximum number of times with the objective to prevent worst solutions during localization. The rate of localization achieved through the enforcement of the proposed ROA-APS is identified to be considerably improved by 7.94%, 9.42%, 11.52% and 13.96% when compared to the benchmarked DVBAWI-NLS, CVP-NPS, DRSS-NLS and BPCLA schemes considered for investigation. Likewise, the localization error of the proposed ROA-APS for different number of NLOS nodes is determined to be considerably reduced by 10%, 13% and 17% when compared to DVBAWI-NLS, CVP-NPS, DRSS-NLS and BPCLA schemes considered for investigation.

In the third fold of investigation, the potential of the proposed ROA-APS and the benchmarked DVBAWI-NLS, CVP-NPS, DRSS-NLS and BPCLA approaches is explored for varying number of reference nodes in the network. Figures 10 and 11 exemplar the plots of percentage improvement in the emergency message dissemination rate and the percentage increase in the NLOS nodes localization rate attained by the proposed ROA-APS and the DVBAWI-NLS, CVP-NPS, DRSS-NLS and BPCLA approaches for different number of reference nodes. The percentage improvement in the emergency message dissemination rate for varying number of reference nodes is determined to comparatively higher than the benchmarked schemes, since the proposed ROA-APS establishes two different population zones and radius in order to balance the degree of exploitation and exploration during the process of localization. Likewise, the percentage increase in the NLOS nodes localization rate achieved by the proposed ROA-APS is confirmed to be superior independent of the number of reference nodes used for localizing NLOS nodes. The percentage improvement in the emergency message dissemination rate achieved by the proposed ROA-APS is identified to be considerably minimized by 6.21, 7.94%, 9.16% and 11.28% when compared to the benchmarked DVBAWI-NLS, CVP-NPS, DRSS-NLS and BPCLA schemes considered for investigation. The percentage increase in the NLOS nodes localization rate facilitated by the proposed ROA-APS for varying number of reference nodes is considered to be reduced by 6.94%, 7.64%, 8.94% and 9.42% in contrast to the baseline DVBAWI-NLS, CVP-NPS and DRSS-NLS and BPCLA schemes used for investigation.

In addition, Figs. 12 and 13 present the percentage decrease in energy consumption for localizing NLOS nodes and percentage decrease in latency of emergency message for varying number of reference nodes ensured by the proposed ROA-APS on par with DVBAWI-NLS, CVP-NPS, DRSS-NLS and BPCLA approaches. The percentage decrease in energy consumption for localizing NLOS nodes and percentage decrease in latency of emergency messages for varying number of reference nodes attained by the proposed ROA-APS is highly reduced, since it incorporates

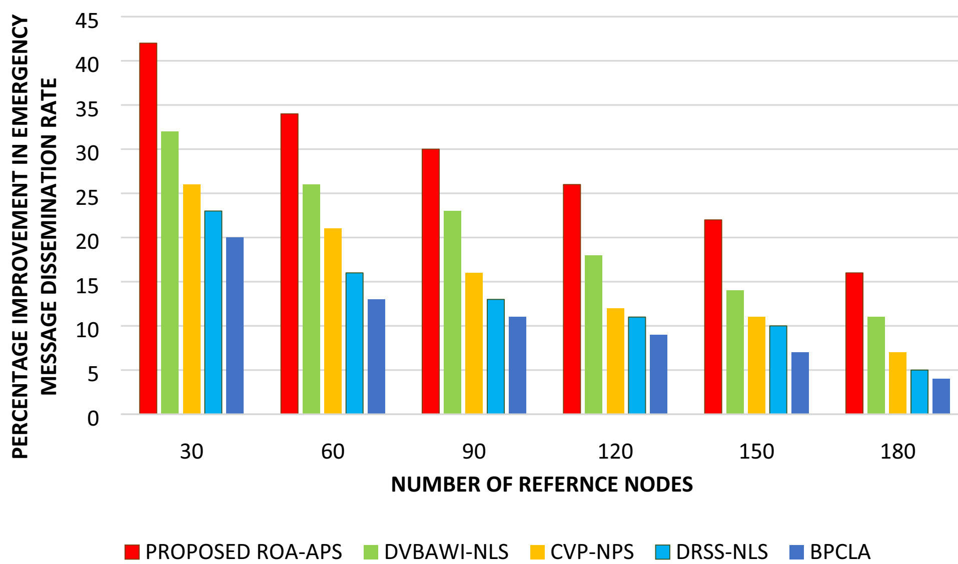

Fig. 10 Percentage improvement in the emergency message dissemination rate of the proposed ROA-APS for varying number of reference nodes

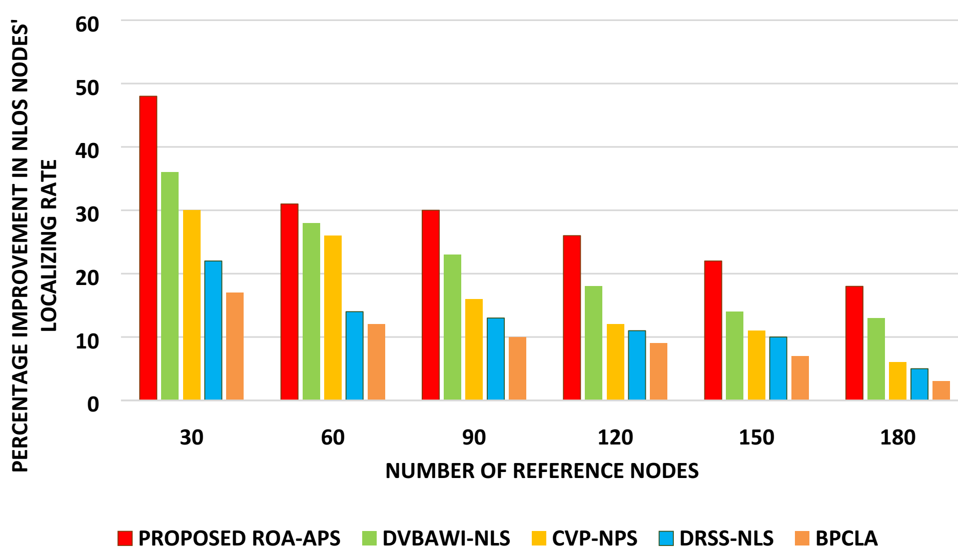

Fig. 11 Percentage increase in the NLOS nodes' localization rate of the proposed ROA-APS for varying number of reference nodes

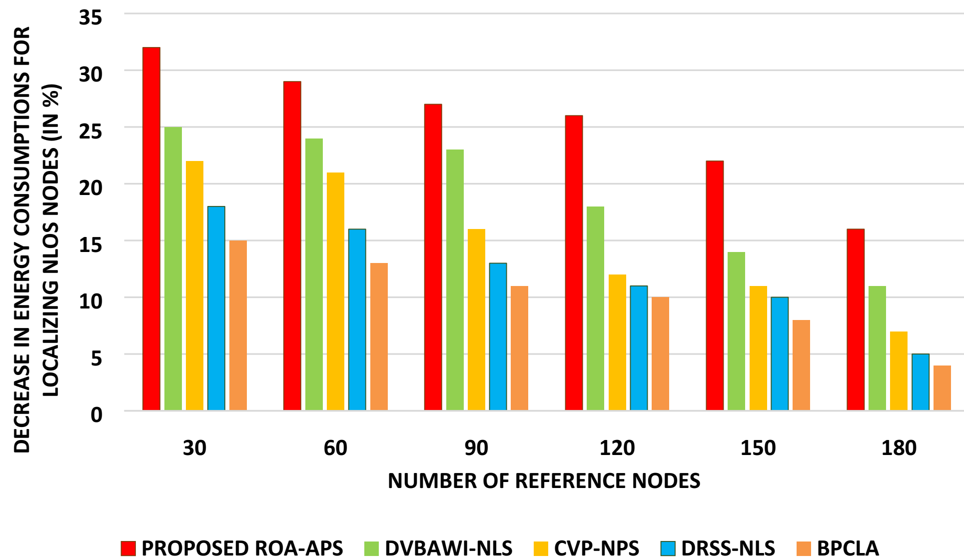

Fig. 12 Percentage decrease in energy consumption for localizing NLOS nodes of the proposed ROA-APS for varying number of reference nodes

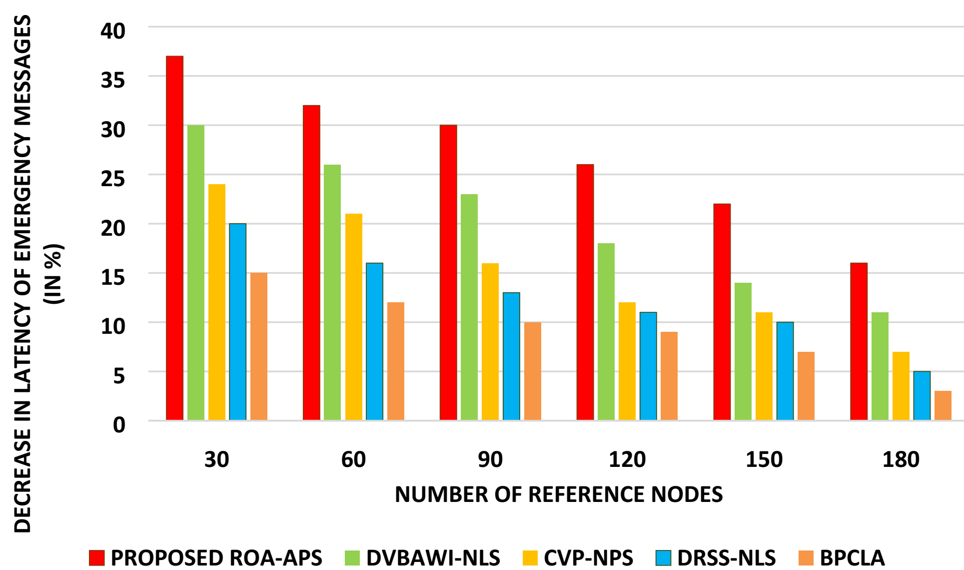

Fig. 13 Percentage decrease in latency of emergency message of the proposed ROA-APS for varying number of reference nodes

the preservation factors that reduce the number of reference nodes used for localization. This in turn leads to minimized delay in warning message delivery in the network. The percentage decrease in energy consumption for localizing NLOS nodes achieved by the proposed ROA-APS is identified to be considerably minimized by 7.92%, 8.84%, 9.16% and 10.52% when compared to the benchmarked DVBAWI-NLS, CVP-NPS, DRSS-NLS and BPCLA schemes considered for investigation. The percentage decrease in latency of emergency message achieved by the proposed ROA-APS for varying number of reference nodes is considered to be reduced by 5.42%, 6.79%, 8.74% and 9.94% in contrast to the baseline DVBAWI-NLS, CVP-NPS and DRSS-NLS and BPCLA schemes used for investigation.

5 Conclusion

The proposed ROA-APS is contributed as a reliable attempt to position NLOS nodes based on the intelligent rummaging style of raccoon search agents more precisely. This proposed ROA-APS facilitates maximized localization rate with reduced localization error during the dissemination of warning messages. It is proposed with the merits of PRZ and PVZ and its associated radius for ideal localization of NLOS nodes with the view to improve the warning message delivery rate, awareness rate and degree of channel utilization in the event of emergency situations. In specific, the preservation and migration factors play an anchor role in balancing the tradeoff between exploitation and exploration that results in efficient NLOS localization process independent of the location of NLOS nodes from the location of reference nodes. The simulation results of the proposed ROA-APS demonstrate an improvement in the mean warning message delivery rate by 13.28% and mean neighborhood awareness rate by 12.84% for varying densities of vehicular nodes compared to the baseline DVBAWI-NLS, CVP-NPS, DRSS-NLS and BPCLA schemes considered for investigation. This proposed ROA-APS is identified to enhance the localization rate by 14.21% and minimize the localization time by 13.94% when compared to the benchmarked schemes considered for exploration. Further, the delivery rate of warning messages and rate of awareness introduced by the proposed ROA-APS with increasing reference nodes also prove to be excellent by 10.95% and 11.34% when compared to the baseline schemes taken for investigation. In the near future, it is also planned to formulate and implement an integrated simulated annealing and spotted hyena algorithm for NLOS node positioning in order to compare them to determine the superior technique of both the algorithms.

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