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An Improved DV-HOP Localization Technique via VVS-HCO for Wireless Sensor Networks

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Abstract: Wireless Sensor Networks (WSNs) are a core enabler of applications such as environmental monitoring, military surveillance, and smart city infrastructure, where precise node location high quality location estimation is of paramount importance. This paper proposes an improved localization scheme for WSN sensor nodes, where the DV-Hop range free localization scheme estimations are optimized via the variable velocity strategy (VVS) and human conception optimization (HCO) techniques. The proposed technique is evaluated via building a wireless sensor network (WSN) with realistic constraints that are included using simulations, so that the nature of the wireless communication channel and its impact on estimation accuracy is exploited. The effect of noise and the RF wireless channel and on the localization, algorithms are included in the simulations. The experimental results show that the proposed DV-HOP-VVS-HCO outperforms the standard DV-Hop technique by about 11% to 13% at moderate SNR values. The proposed algorithm is more adaptable to the sensor to anchors counts and of course the topology changes. The results indicate that the proposed DV-HOP-VVS-HCO model is more robust than the standard DV-Hop and can withstand the increase in the node populations and density. The DV-HOP-VVS-HCO achieves better means of localization error with percentage improvement of about 23% as compared to DV-Hop especially at denser WSNs.

Keywords: DV-Hop, VVS, HCO, WSN, Node Localization, Range free Localization, Localization Accuracy.

1. Introduction

Wireless Sensor Networks (WSNs) are networks of numerous sensor nodes that communicate wirelessly for measuring information about their environment. These networks should be cost effective, energy-efficient, and flexible. WSNs are important in many applications such as environmental monitoring, military surveillance, traffic control, healthcare, and industrial automation [1, 2]. Knowing the exact locations of the sensor nodes is crucial, because data without location information is usually meaningless [3,4].

Node localization in Wireless Sensor Networks (WSNs) is also important for many aspects including efficient routing, data delivery, target tracking and monitoring. Self-Organization, Network Management, Data Fusion and Recovery, Data Validation and Cleansing, Clustering and Routing, Controlled Energy, Efficient Routing, Security and Authentication are also dependent on WSN node accurate localization.

Localization in WSNs can be realized using different techniques which can be divided into range-based and range-free techniques. Range-based techniques based on accurate distance or angle measurements but require employment of additional hardware like GPS and intensive calculations, that always result in more energy consumption and more expensive [5, 6]. On the other hand, the range-free approaches can estimate node locations via connectivity information, so that they don't require any additional hardware. An example to this category is the Distance Vector Hop (DV-Hop) algorithm [9,16] that can estimate node location based on the hop counts and connectivity, so that they are more economic and energy-efficient [7, 8]. While traditional range-free approaches such as DV-Hop are widely deployed, they have limited localization accuracy because of the erratic communication ranges, different hop distances and the difficulty of anisotropic counter influence factors on localization [9, 10]. In addition, progressive errors in location estimation commonly occur.

Range-free localization algorithms like DV-Hop are appealing as they only require message exchange and hop count information. This results in a lower implementation cost than other range methods. The localization performance is sensitive to network density and anchor distribution. Generally, anchors can always be uniformly distributed to achieve high accuracy. Swarm optimization techniques have also been used to improve the performance of the DV-Hop technique [6], [9] in conjunction with a global search capacity with a local refinement to enhance the estimation accuracy. Combining both human-like reflection and variable velocity techniques incorporates adaptive behavior to the optimization. In addition, by centering the search at the initial DV-Hop estimates, the solution space for the problem is constrained and gibbering in improving the convergence speed.

Numerous attempts to overcome the limitations by different techniques including proposing optimization algorithms based on natural phenomena like Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Ant Colony Optimization (ACO) [11–13]. Through promising approaches, they are frequently confronted with several problems, e.g., convergence rate, local minima issues, and heavy computational loads, which is a crucial aspect for resource-limited WSNs [14, 15]. On the other hand, DV-Hop localization has limitations which are addressed in research and different solutions are proposed. These challenges include estimation accuracy as the DV-Hop accumulates errors over the number of hop distances that are averaged, which degenerates the localization accuracy. Researchers such as Chien-Chung Chen, Shuang Hao, Jianhua Zhang, Pankaj Kumar Garg, Xue Liu and M. Zorzi [6] proposed solutions via hybrid methods, error correction techniques, and improved distance estimations. However, these techniques impact energy consumption, as the network nodes in WSNs became power-starved and hence nodes lose their communication in DV-Hop as a cause for excessive energy consumption, which is solved by Shuang Hao and Mahesh N. S. [7] by proposing energy-efficient DV-Hop enhancements and elimination of the redundant transmissions. Xue Liu, Sudhir S. P., and Jianhua Zhang [9] also dealt with error propagation problem through adaptive hop-count adjustments and combining DV-Hop with other methods, The anchors placement and their count also affect performance of DV-Hop. Poor placement can result in inaccurate localization, as found by Wenyuan Xu, Sudhir S. P., and Pankaj Kumar Garg [7, 9] They could improve localization accuracy by leveraging optimized anchor placement strategies and using more intelligent node selection techniques. The interference, mobility, and dynamic changes can result in less reliable DV-Hop. M. Ilyas, S. K. Das, and M. Zorzi, et al. Zorzi addressed mobility, dynamic hop-count adjustments, and various alternative path estimation techniques; and hybrid approaches to enhance performance. Hybrid localization techniques are proposed by Jianhua Zhang, Pankaj Kumar Garg, and Michele Zorzi by integrating DV-Hop with machine learning, RSSI, or other localization techniques.

In this paper an enhancement for the standard Distance Vector Hop (DV-Hop) scheme is introduced and. In it, an optimization to DV-Hop parameters by using the "Variable Velocity Strategy Human Conception Optimization (VVS-HCO)" optimization algorithm. The technique is named DV-HOP-VVS-HCO due to optimizing DV-Hop using the VVS-HCO optimization algorithm. This proposed technique can overcome the limitations of the pure DV-Hop algorithm and even outperform the existing optimization algorithms by adaptively controlling particle velocity and improving the convergence speed and estimation accuracy as shown in results. Additionally, simplified radio irregularity modelling via imposing AWGN is introduced in the algorithm to accommodate non-isotropic radio propagation characteristics in practical environments. The main contributions of this work can be summarized as follows: 1) Improving DV-Hop precision via Variable Velocity Strategy (VVS-HCO), 2) Hop size adjustment by tuning parameters (like a gain/tuning factor) is introduced to adjust the hop-sizes, providing more accurate distance estimations between nodes. 3) Radio Path Loss (RPL) model is applied within the VVS-HCO to represent the non-uniformity of radio

signals that often distorts the distance estimates (measurements) between the nodes. 4) A realistic modeling for WSN implementation including RF impairments is incorporated in the simulations of the proposed DV-HOP-VVS-HCO technique. In this paper, we propose an Improved Distance Vector Hop (IDV-Hop) algorithm enhanced by a Variable Velocity Strategy Human Conception Optimization (VVS-HCO).
The remainder of this paper is structured as follows: Section 2 describes related work, including current localization approaches along with their shortcomings. In Section 3, the standard DV-Hop technique is described, and the trilateration process is explained. Section 4 is dedicated to the variable velocity strategy (VVS) and human conception optimization (HCO) techniques Section 5 introduces the fusion of DV-Hop and VVS-HCO into the DV-HOP-VVS_HCO proposed optimized localization technique. The network setup can be found in Section 6. The steps adopted for implementing the simulated WSN and the localization scenario via the DV-HOP-VVS-HCO can be found in Section 7. Section 8 is dedicated to the results, and the paper is concluded in Section 9.

2. Related Work

Localization in WSNs plays an important role in many applications including environment monitoring, military surveillance, and smart city systems. Localization techniques can be classified into range-based techniques and range free techniques. Range based techniques include Time of Arrival (ToA), Time Difference of Arrival (TDoA) and Angle of Arrival (AoA). However, these techniques are very accurate, but they are computationally intensive, require additional hardware. These requirements are not suitable in WSNs where the nodes are battery powered and designed to consume minimal energy from their batteries. The other class of the localization techniques is the range free based techniques. They don't require additional hardware and need low computational power [15] that suits WSNs. Various range free localization techniques are deployed, such as DV-Hop, Centroid, APIT, and Amorphous [17]. Also, many hybrids range-free techniques are developed for improving accuracy and energy consumption [19]. DV-Hop attracts the attention for its simplicity and moderate accuracy as compared to other range free methods [16]. However, the traditional DV-Hop has a limited localization accuracy in the anisotropic environment, since the unpredictable communication range, and varying hop size would distort distance estimation [17]. To overcome these limitations, many enhancements for the DV-Hop algorithm have been suggested. For instance, Duan et al. enhanced DV-Hop by randomly deploying the reference nodes to cover the entire monitored region and utilizing PSO to minimize the localization error. Adding anchor nodes to the system will improve accuracy but it will not be more efficient in large and remote environment because of the requirement of the anchor node placement as in [18]. Similarly, Panda et al. proposed a reasonably power-efficient range-free localization system in which beacon nodes simply introduce their information and all other unknown nodes estimate their hop counts. This approach reduces energy consumption; however, it suffers from an inaccuracy problem when the nodes are not distributed uniformly in wireless sensor network [19].
Sun et al. [10] introduced a distributed range-free localization algorithm in which unknown nodes use local information to infer their locations and thus reduce message delivery and energy consumption. However, this approach does not consider transmission disparities and can be used to derive inconsistent results in practice [20]. Wu et al. improved DV-Hop based on the genetic algorithm (GA) approach, adjusting hop sizes with a factor and fine tuning them by the line search procedure. Although this increases accuracy, it is computation ally intensive and can be suboptimal for sparsely or nonuniformly distributed node deployments [21]. Table 1 summarizes the findings of some recent studies.
Other optimization methods including GWO (Grey Wolf Optimization) and CTO (Class Topper Optimization) were also used to improve DV-Hop. Palanisamy et al. employed the GWO to estimate the per hop standard deviation, obtaining more accurate results with a slight growth on computational cost [22]. Nandan et al. incorporated CTO to DV-Hop and the introduction of a scaling factor to modify the hop size and enhance localization accuracy. However, they usually fail to converge in multi-agent systems in a complex or dynamic environment [23]. The current trends have been hybrid methodologies. Lakshmi et al.

complemented PSO with DV-Hop to calculate distances based on the hop size that was between anchor nodes, and to enhance localization accuracy [24]. Ghadami et al. suggested an RRO-based DV-Hop, where they adapted the hop sizes by a correction factor and further by means of a line search method [25]. Although these techniques are promising, they are too computationally intensive or not effective for anisotropic conditions.

To mitigate these shortcomings, researchers have investigated multi-objective optimization and improved algorithms. Yu et al. presented DV-Hop method of nsga II by imposing constraints on anchor nodes to increase the accuracy [26]. Li et al. employed multi-objective functions for minimizing model size and performing global optimization [27]. Additionally, Wang et al. proposed a PCWOA algorithm to improve DV-Hop localization by reducing the memory consumption and improve the accuracy of the solutions [28].

Notwithstanding these advancements, challenges persist, in particular, for processing anisotropic cases and lowering the computational burden. Ma et al. enhanced DV-Hop algorithm, in which by correcting the single-hop distances with the RSSI values and by adapting the 16average hop distances based on the real differences and the estimated ones [29]. Drakoulas et al. combined 2D Hyperbolic Localization Method with Improved Adaptive Genetic Algorithm (IAGA) for more accurate estimation in anisotropic networks [30]. However, such approaches generally depend on additional hardware and complex computations, which are less practical to be used in resource-limited WSNs.

In conclusion, although some achievements have been made into DV-Hop and other range-free algorithms, several issues remain outstanding. They suffer from poor accuracy in anisotropic media, high complexity, and the potential existence of local optima in optimization-based methods. In an effort to fill these gaps, an improved DV-Hop algorithm that incorporates Variable Velocity Strategy Human Conception Optimization (VVS-HCO) and a Radio Irregularity Model is proposed in this paper. By adaptively tuning the actual rate of optimization, this method can achieve dynamic optimization speed changes, enabling convergence acceleration and accuracy improvement in real-world, irregular environments, and thus outperforms all tested existing approaches in terms of localization error, variance, and accuracy. The recent developments on DV-Hop localization are summarized in Table 1.

Table 1: An Overview of Recent DV-Hop Localization Enhancement Evolution.

Article	Year	Techniques	Contributions	Limitations
Liu et al. [10]	2024	DV-Hop with Neural Networks	Improved localization accuracy using neural networks for distance estimation.	High computational cost; requires large training datasets.
Zhang et al. [33]	2024	DV-Hop with Whale Optimization Algorithm (WOA)	Improved convergence speed and accuracy in large-scale networks.	Limited performance in anisotropic environments.
Lei et al. [34]	2024	DV-Hop with Sparrow Search Algorithm (SSA)	Reduced localization error by optimizing hop sizes using SSA.	Computationally intensive; struggles with dynamic node movements.
Mani et al. [35]	2024	DV-Hop with Adaptive Genetic Algorithm (AGA)	Enhanced accuracy by dynamically adjusting GA parameters.	High computational overhead; struggles with irregular node placement.
Ma et al. [37]	2024	DV-Hop with RSSI and Least Squares Method	Corrected single-hop distances using RSS I, improving accuracy.	Requires additional hardware; struggles with signal interference.
Cao et al. [38]	2024	DV-Hop with 2D Hyperbolic Localization and IAGA	Enhanced accuracy in anisotropic networks using adaptive GA.	Computationally intensive; struggles with irregular signal propagation.

Article	Year	Techniques	Contributions	Limitations
Singh et al. [32]	2025	DV-Hop with Reinforcement Learning (RL)	Enhanced accuracy by dynamically adjusting hop sizes using RL.	Struggles with sparse networks; high energy consumption.
Yang et al. [35]	2025	DV-Hop with Grey Wolf Optimization (GWO)	Improved precision by predicting standard deviation per hop using GWO.	Marginal increase in computational cost; struggles with sparse networks.

Efficient operation of the network requires accurate localization of sensor nodes, which have several applications: environmental monitoring, disaster management, intelligent transportation system, etc. Traditional localization, such as DV-Hop and RSSI-based localization, are error prone for signal interference, environmental noises, and the network irregular topologies. To cope with these issues, a proposed method in this paper combines DV-HOP and Variable Velocity Strategy with Human Conception Optimization (VVS-HCO) to improve location estimation accuracy of sensor nodes. In the following part, a description of that novel localization technique is introduced.

3. Localization via the DV-HOP algorithm

DV-HOP operates in three phases:

1. Hop Count Propagation: Anchor nodes broadcast their positions, and other nodes record the minimum hop counts.
2. Average Hop Distance Calculation: Anchors compute the average distance per hop based on known positions.
3. Position Estimation: Unknown nodes use trilateration or multilateration to estimate their locations.

3.1 Mathematical Formulation of DV-HOP

3.1.1 Hop Count Propagation

Each anchor node i broadcasts its position (x_i, y_i) along with a hop count initialized to 0. Neighboring nodes increment the hop count and forward the message. The minimum hop count h_{ij} from anchor i to node j is recorded.

3.1.2 Average Hop Distance Calculation

The Average Hop Distance (AHD) is determined using anchor nodes with known positions. It is calculated as the ratio of the sum of actual distances between anchor pairs to the corresponding sum of hop counts between them:

Anchors compute the average hop distance (AHD_i) to the node i as in (1):

$$AHD_i = \frac{\sum_{j\neq i}\sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2}}{\sum_{j\neq i} h_{ij}} \tag{1}$$

where $\left(x_j, y_j\right)$ are the positions of other anchors, and h_{ij} is the hop count between them and,

$$d_{ij} = \sqrt{\left(x_j - x_i\right)^2 + \left(y_j - y_i\right)^2} \tag{2}$$

where d_{ij} is the Euclidean distance between any two nodes i, j

Accurate distance estimation in wireless sensor networks (WSNs) relies on the relationship between hop counts and actual physical distances. Since hop count-based localization assumes uniform node distribution and ideal transmission conditions, real-world factors such as irregular node spacing, varying transmission ranges, and environmental interference introduce deviations. To address these uncertainties, the AHD is computed to provide a more precise correlation between hop counts and Euclidean distances. This formulation ensures that the computed hop distance reflects the spatial distribution of nodes while reducing estimation bias.

Once AHD is determined, it is utilized to estimate the distance, $\hat{d}_i$, between an unknown node and an anchor node as shown in (3):

$$\hat{d}_i = AHD_i \times h_i \quad (3)$$

This serves as an initial estimate of node locations before applying further refinement techniques. Since real-world networks are subject to signal attenuation and interference, errors may arise in hop-based distance estimation. To mitigate these inaccuracies, an adaptive correction factor is introduced as shown in (4):

$$\hat{d}_i^{\,corr} = AHD_i + \kappa \quad (4)$$

where κ is a correction factor that can be adjusted using an optimization technique for enhancing the estimation accuracy and $\hat{d}_i^{\,corr}$ denotes the corrected estimated distance.

3.2 Trilateration for DV-Hop based estimations

Using trilateration, the coordinates (x, y) of an unknown node can be found by solving the least-squares problem:

$$Ax = b \quad (5)$$

where

$$A = 2\begin{pmatrix} x_n - x_1 & y_n - y_1 \\ x_n - x_2 & y_n - y_2 \\ \cdots & \cdots \\ x_n - x_{n-1} & y_n - y_{n-1} \end{pmatrix}$$

and

$$b = \begin{pmatrix} x_n^2 - x_1^2 + y_n^2 - y_1^2 + d_1^2 - d_n^2 \\ x_n^2 - x_2^2 + y_n^2 - y_2^2 + d_2^2 - d_n^2 \\ \cdots \\ x_n^2 - x_{n-1}^2 + y_n^2 - y_{n-1}^2 + d_{n-1}^2 - d_n^2 \end{pmatrix}$$

The solution for the required location $X = (x, y)$ of a node is obtained via:

$$X = (A^T A)^{-1} A^T b \quad (6)$$

where $(.)^T$ is the transpose operator for a matrix, $(.)^{-1}$ denotes the inverse of a matrix.

4. Variable Velocity Strategy with Human Conception Optimization (VVS-HCO)

This optimization algorithm can be considered an enhancement of the well-known Particle Swarm Optimization (PSO) technique [9, 36]. Numerous studies implemented PSO in enhancing the DV-Hop based localization [9, 36].

The difference between VVS-HCO and the standard PSO can be summarized as follows [19, 39]:

1. Variable Parameters: VVS-HCO uses time-varying inertia, oscillating cognitive weights, and increasing social weights, while standard PSO uses fixed parameters
2. Human Conception: VVS-HCO includes knowledge pools, learning transfer, and self-reflection mechanisms that standard PSO lacks
3. Rank-Based Adaptation: VVS-HCO adjusts behavior based on particle performance ranking
4. Early Stopping: VVS-HCO has human-like intuitive stopping criteria

4.1 Velocity Update Mechanism

The velocity of particle i at iteration $+1$, $v_i^{t+1}$is updated using Equation (7):

$$v_i^{t+1} = w(\tau) * v_i^t + c_1 * r_1 * \left(p_{best,i} - x_i^t\right) + c_2 * r_2 * (g_{best} - x_i^t) + \alpha * V_{var}(\tau) \quad (7)$$

Where v_i^{t+1} is the updated particle velocity, $w(\tau)$ is the time-varying inertia weight , c_1, c_2 are acceleration coefficients , r_1, r_2 are random numbers in [0,1], $p_{best,i}$ is the personal best position of particle i , and $g_{best}$is the global best position, t is the iteration number, and τ represents the time.

4.1.1 Time-Varying Inertia Weight

Equation (8) shows how the inertia weight $w(\tau)$is updated through runtime τ as:

$$w(\tau) = w_{max} - \left((w_{max} - w_{min}) * \tau\right)/T_{max} \tag{8}$$

Where $w_{max} = 0.9, w_{min} = 0.4$ (are typical values) and T_{max} is the maximum number of iterations.

4.1.2 Variable Velocity Component

The particle velocity variation, $v_{var}(\tau)$, in the algorithm follows an exponential decaying sinusoidal as shown in Equation (9)

$$V_{var}(\tau) = \beta * sin\left(2\pi * \tau/T_{period}\right) * exp(-\gamma * \tau/T_{max}) \tag{9}$$

Where β is the amplitude scaling factor, T_{period} is the oscillation period and γ is the decay coefficient.

4.2 Human Conception Optimization (HCO)

The HCO is designed to follow a Cognitive Learning Factor (CLF) [19], $C_L(\tau)$ as represented in Equation (10)

$$C_L(\tau) = C_{L,max} * exp(-\delta * (f_{current} - f_{best})/f_{best}) \tag{10}$$

Where:

$C_{L,max}$ is the maximum cognitive learning factor

δ is the cognitive decay parameter

$f_{current}$ is the current fitness value

f_{best} is the best fitness value found so far.

It also defines a Social Learning Factor (SLF), $S_L(\tau)$, as described in Equation (11)

$$S_L(\tau) = S_{L,min} + \left(S_{L,max} - S_{L,min}\right) * \left(1 - exp(-\varepsilon * \tau/T_{max})\right) \tag{11}$$

Where:

$S_{L,max}, S_{L,min}$ are maximum and minimum social learning factors

ε is the social learning growth parameter

4.3 Modified Velocity Update with HCO

$$v_i^{t+1} = w(\tau) * v_i^t + C_L(\tau) * r_1 * \left(p_{best,i} - x_i^t\right) + S_L(\tau) * r_2 * (g_{best} - x_i^t) + \alpha * V_{var}(\tau) + H_i(\tau) \tag{12}$$

Where $H_i(\tau)$ is the human conception component that is given by Equation (13):

$$H_i(\tau) = \eta * tanh\left(\zeta * \left(f_{avg} - f_i(\tau)\right)\right) * (x_{random} - x_i^t) \tag{13}$$

Where:

η is the human conception strength parameter

ζ is the sensitivity parameter

f_{avg} is the average fitness of the population

$f_i(\tau)$ is the fitness of particles i at iteration t

x_{random} is a randomly selected position from elite particles

α is the variable velocity coefficient

$V_{var}(\tau)$ is the variable velocity component

4.4 Fitness Function for Node Localization

The Primary Objective Function (POF), $F_1(x_i, y_i)$, is structured as in Equation (14)

$$F_1(x_i, y_i) = \sum \left(\hat{d_{ij}} - \sqrt{\left((x_i - x_j)^2 + (y_i - y_j)^2\right)}\right)^2 \tag{14}$$

Where M is the number of anchor nodes with known positions and $\hat{d_{ij}}$ denotes the estimated distance. Also, a regularization term $F_2(x_i, y_i)$ is defined as in Equation (15)

$$F_2(x_i, y_i) = \lambda * \sum \left|\hat{d_{ik}} - \sqrt{((x_i - x_k)^2 + (y_i - y_k)^2)}\right| \tag{15}$$

Where:

N_i is the set of neighboring nodes of node i

λ is the regularization parameter

Hence a Combined Fitness Function (CFF), $F(x_i, y_i)$, is defined as in Equation (16):

$$F(x_i, y_i) = F_1(x_i, y_i) + F_2(x_i, y_i) \tag{16}$$

5. The proposed DV-HOP-VVS-HCO localization algorithm

This section introduces the step of fusion between DV-Hop and VVS-HCO.
In this stage, the position estimated by the DV-Hop is optimized and corrected via the VVS-HCO algorithm according to the following Equations (17)-(20):

$$x_i^{t+1} = x_i^t + v_{ix}^{t+1} \tag{17}$$

$$y_i^{t+1} = y_i^t + v_{iy}^{t+1} \tag{18}$$

$$x_i^{t+1} = max\left(x_{min}, min\left(x_{max}, x_i^{t+1}\right)\right) \tag{19}$$

$$y_i^{t+1} = max\left(y_{min}, min\left(y_{max}, y_i^{t+1}\right)\right) \tag{20}$$

where v_{ix}^{t+1} and v_{iy}^{t+1} are the optimized corrections for x_i, y_i, respectively and obtained via the VVS-HCO optimization technique.
The WSN network setup and the proposed approach have been built using Python. The simulation has several stages, including the network description and parameter establishment, in network wise and geometrical wise. To simulate the wireless RF communication between network elements, a standard RF path loss model is employed. Also, the RF signal is assumed to be contaminated with additive white Gaussian noise (AWGN) with zero-mean and variance σ_N . It is also assumed that hop distance calculations are susceptible to AWGN that will reflect on the average hop distance. Figure 1. shows the block diagram of the proposed VVS-HCO-DV-HOP range free localization system.

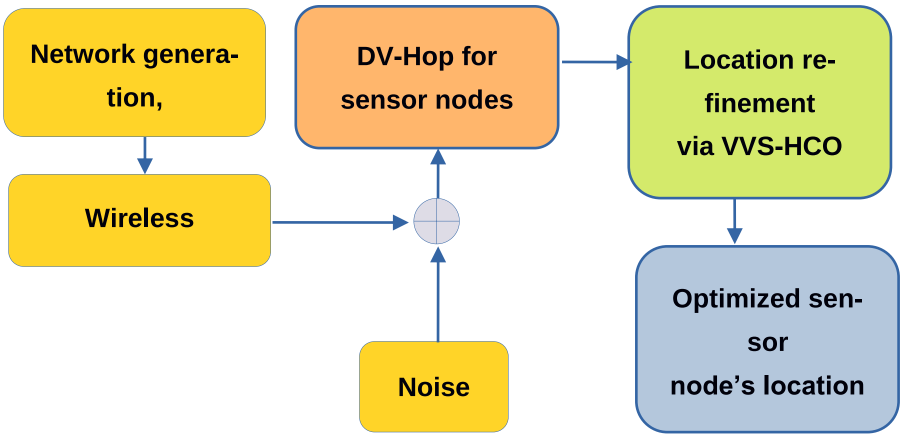

Figure 1: DV-HOP-VVS-HCO range free proposed localization system.

6. Network Parameters and Setup

The proposed WSN implementation topology is represented by a collection of N sensor nodes randomly deployed over a given WSN coverage area. Each node is only equipped with an RF transceiver that allows them to share information within the network. Each RF transceiver has a predefined communication range. The density of nodes has an important impact on not only the localization accuracy, but also the connectivity property of the network.
The spatial density of sensor nodes, ρ, in the deployed area and is defined in mathematical form as the ratio of the overall number of deployed sensor nodes, N, to the total network area, A. This density measurement leads to the information of sparsity, or congestion, of the nodes, hence the communication range and the localization robustness. The density is given by:

$$\rho = \frac{N}{A} \tag{21}$$

It should be noted that: if a node has insufficient neighboring anchor nodes (references) to locate itself, it may be not able to estimate its location. Hence more connectivity of the network will decrease the probability of unlocalized nodes.

Another influential factor in the network topology design is the average node degree, which characterizes the average number of neighbor nodes that one node can directly communicate with. This factor is a function of the transmission range, , as well as the spatial density of nodes, ρ. Average degree, D_{avg} , is calculated as:

$$D_{avg} = \rho \cdot \pi R^2 \tag{22}$$

which establishes a direct correspondence between communication range and networks connectivity. Larger the node degree the more robust is the localization algorithms since there are more reference points available to estimate distance. However, an overly high degree can raise computational complexity and energy consumption as the message exchange might be redundant.

Geometrical relations between network elements are an initial phase in the process of node localization, where spatial related information between the nodes in WSN is inferred.

Distance between any pair of nodes indicates their spatial separation and is necessary to estimate hop based or range-based localization algorithms. If there are two sensor nodes having coordinates (x_i, y_i) and (x_j, y_j), respectively, the inter-node distance can be expressed via Equation (2).

6.1 Node Placement and Mutual Exclusion

The WSN nodes and anchors are assumed to be distributed randomly within the WSN coverage area. A minimum distance, l_{nn} between any two nodes is kept avoiding node/node, node/anchor, or anchor/anchor overlapping.

$$l_{nn} = \mu . W \tag{23}$$

where μ is a factor less than 1 and W is the minimum width of the WSN coverage area.

In wireless sensor networks, the spatial distribution of nodes plays a critical role in ensuring accurate localization and maintaining network connectivity. To prevent node clustering and overlapping, a mutual exclusion constraint is enforced during the node deployment phase. This constraint ensures that each sensor node maintains a minimum separation distance l_{nn} from all other nodes in the network, preventing excessive proximity that could lead to unreliable distance estimations and localization errors.

If Equation (23) is violated so that $d_{ij} < l_{nn}$, indicating that two nodes are positioned too close to each other, the affected node is reassigned a new random position within the network's defined area. This reallocation process continues iteratively until all nodes comply with the minimum separation requirement of Equation (23).

This constraint is called the mutual exclusion which ensures a more uniform node distribution, reducing the likelihood of localization ambiguities caused by overlapping nodes. By maintaining sufficient separation, the network topology remains well-structured, enabling robust connectivity and improving the performance of the subsequent hop-count-based and machine learning-driven localization processes.

6.2 Hop Count Calculation with AWGN

The hop count calculation serves as a fundamental step in distance estimation for localization in WSNs. Since not all nodes have direct access to anchor nodes with known positions, multi-hop communication is employed to approximate distances based on intermediate node connections. The hop count h_{ij} is determined by evaluating the number of transmission hops required for a packet to travel from an anchor node to a given unknown node. This approach provides an initial estimate of distances, which is later refined using machine learning and optimization techniques.

The estimation of hop counts relies on a Breadth-First Search (BFS) algorithm [], which systematically explores all neighboring nodes before moving to the next level of connectivity. The process begins with each anchor node initializing a hop count value of zero and broadcasting a control packet containing its identification and hop count to all one-hop neighbors. Upon receiving this packet, each neighboring node

records the hop count and forwards the packet to its own neighbors after incrementing the hop count value. Nodes that have already received a hop count value discard duplicate packets to prevent redundant updates. This iterative process continues until all nodes in the network have recorded the minimum hop count to the nearest anchor node.
The hop count h_{ij} from an anchor node i to an unknown node j is updated iteratively as:

$$h_{ij} = min(H_{ik} + 1), \forall k \in N(j) \tag{24}$$

where $N(j)$ represents the set of the neighboring nodes of j, and H_{ik} is the hop count for node k. Since BFS guarantees that each node records the shortest hop count to the nearest anchor, this approach provides an efficient means of estimating connectivity-based distances.
While BFS-based hop counting provides a structured approach for distance estimation, signal degradation, multipath interference, and environmental factors introduce uncertainties that necessitate the incorporation of an Additive White Gaussian Noise (AWGN) model. To account for real-world signal distortions and propagation losses, the received power at a given node is modeled using the channel path loss model in Equation (25). The received signal power $P_r dB$ at a distance d from a transmitting node that transmits at power of $P_t dB$ is expressed as:

$$P_r = P_t - 10nlog_{10}(d) + X_\sigma \tag{25}$$

where the parameter n is the path-loss exponent, which varies based on environmental conditions such as open spaces, urban areas, or indoor settings. Additionally, X_σ accounts for the noise component and follows a Gaussian distribution.
The presence of AWGN introduces uncertainty in the hop count calculation, leading to discrepancies between the estimated and actual distances. These discrepancies manifest in different ways depending on network conditions. In high-noise environments, packet losses may cause nodes to miss transmissions, resulting in an underestimation of the hop count. Conversely, signal fading and interference may necessitate additional re-transmissions, leading to an overestimation of the hop count. These variations contribute to inaccuracies in distance estimation, highlighting the need for refined computational models to mitigate such effects. The probability of successful packet reception P_{rx} in the presence of AWGN can be expressed as:

$$P_{rx} = Q\left(\frac{SNR_r - SNR_{th}}{\sigma}\right) \tag{26}$$

$Q(.)$ represents the Q-function, which describes the tail probability of the Gaussian distribution. The parameter SNR_r denotes the received signal-to-noise ratio, while SNR_{th} represents the threshold SNR required for successful packet decoding. Additionally, σ corresponds to the standard deviation of noise fluctuations. When the packet reception probability P_{rx} drops below a critical threshold, the effective hop count increases due to the necessity of packet retransmissions and the introduction of additional intermediate hops.
Once hop counts are established, the average hop distance (AHD) is computed to approximate physical distances between nodes according to Equation (1) and consequently the estimated distance can be found using Equation (3).

7. The DV-HOP-VVS-HCO implementation and performance evaluation

For evaluating the proposed DV-HOP-VVS-HCO localization technique, a simulation of the system is built via Python. The simulation scenario is divided into six phases. Phase 1: "Network initialization" in which the WSN parameters are set such as the area, wireless environment, and RF transmission parameters within the WSN area. Phase 2: "Network deployment" where sensor nodes and anchors are placed within the WSN area. In this simulation, the distribution is totally random for both types of nodes. Phase 3: "DV-Hop processing" is the stage at which the hop counts and hop distances for each sensor node in networks are calculated. In addition, an AWGN is imposed to RF signals to cause errors in estimations. In Phase 4: "Sensor localization", the DV-Hop algorithm is applied to calculate the distances from anchors to each sensor node.

In this stage the RF communication constraints are applied to determine the nearest anchors for each node. It is required that at least three neighboring anchors are seen by every sensor node. Triangulation is then applied to estimate the non-optimized locations or coordinates of each sensor. Phase 5: "VVS-HCO Optimization" is the stage in which the estimated non-accurate node locations are refined and optimized via the VVS-HCO optimization algorithm. This is the core enhancement for mitigating the errors in location estimation. Finally in Phase 6: "Performance evaluation", the deviation from the true locations for sensors that set in Phase 2 is calculated to report the extent of enhancements via deploying the DV-HOP-VVS-HCO algorithm. The performance evaluation is obtained via calculating the root mean square error (RMSE). The system performance is evaluated over a range of SNRs to evaluate the robustness and superiority of the proposed algorithm versus the DV-Hop technique.
The RMSE is averaged for all the locations of the sensors to find the mean localization error (MLE). RMSE is calculated according to Equation (27)

$$RMSE = \sqrt{(x_{true} - x_{estimated})^2 + (y_{true} - y_{estimated})^2} \tag{27}$$

where (x_{true}, y_{true}) represents the true position of the node, and $(x_{estimated}, y_{estimated})$ is the estimated position.
The MLE is calculated via Equation (28).

$$MLE = \frac{1}{N}\sum RMSE_i \tag{28}$$

where $RMSE_i$ is a node-wise, i.e. the RMSE for sensor node i, while MLE is a network-wise.
The network parameters selected for testing and evaluation the DV-HO-VVS-HCO algorithm is as follows: WSN occupies an area of $10000m^2$, and the number of anchors and sensors are initially set to 20 and 100 respectively. The transceiver RF range is set to $20m$. The anchors and sensors are distributed randomly within the area. The SNR is varied from $0dB$ to $30dB$. The simulations are averaged for 10 runs per SNR level. The transceiver sensitivity is set to $-85dBm$ that is a common value. Table 2 summarizes the settings of the simulations.

Table 2: Simulation settings

Parameter	Area	RF communi-cation range	Transceiver sensitivity	Number of anchor nodes	Number of sensor nodes	SNR (dB)
Value	100m x 100m	20m	-85 dBm	20	20 - 200	0 - 30

This scenario is challenging and crucial for node localization. In addition, a low RF range is assumed to further test the proposed DV-HOP-VVS-HCO localization algorithm under these harsh conditions.

8. Simulation Results

In this section, the results obtained from running the simulation of the WSN that is equiped by the proposed localization technique is introduced. Both DV-Hop and DV-HOP-VVS-HCO localization techniques are tested and evaluated while applying a realistic RF communication channel model within the WSN. The settings for important simulation parameters are found in Table 2. The performance evaluation is done via measuring the root mean square error (RMSE) and deducing the mean localization error (MLE). The SNR and number of nodes are changed to find there impact on the localization accuracy.

8.1 The Effect of SNR on MLE

Figure 2 illustrates the impact of signal-to-noise ratio (SNR) on the localization accuracy of two algorithms: Standard DV-Hop and the DV-HOP-VVS-HCO. The Y-axis represents the mean localization error (MLE) in meters, while the X-axis denotes SNR values ranging from 0 dB to 30 dB. Both algorithms exhibit a significant decrease in RMSE as SNR increases, indicating better localization accuracy under lower noise conditions. The standard DV-Hop has an MLE of $30m$ initially at $0dB$ and decreases progressively to around $11.7m$ at $30dB$. Meanwhile, the DV-HOP-VVS-HCO consistently outperforms the benchmark, starting from 29 meters and obtaining an MLE near 10.5 meters at higher SNRs. It should be noted that as SNR increses, the hop size estimations and hop counts become more accurate that leads to better estimation accuracy and hence lower RMSE.

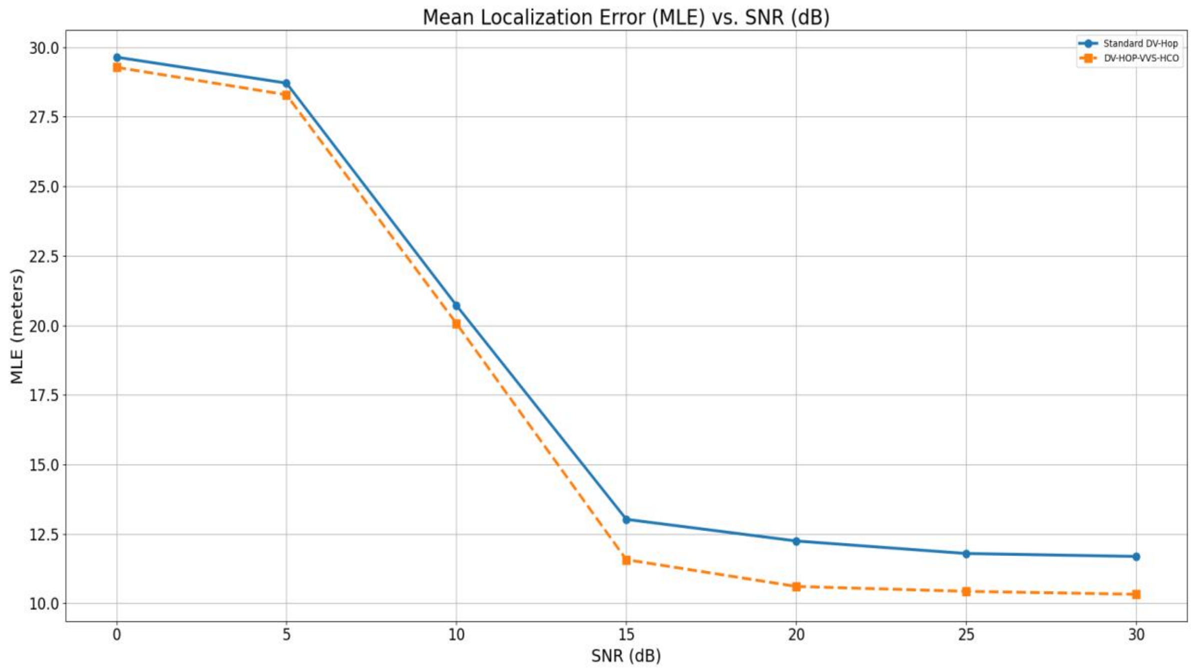

Figure 2: MLE vs. SNR for standard DV-Hop and DV-HOP-VVS-HCO

Table 3: MLE vs. SNR for standard DV-Hop and DV-HOP-VVS-HCO and percentage MLE improvement

SNR (dB)	DV-Hop MLE	DV-HOP-VVS-HCO MLE	% Improvement	SNR (dB)
0	29.65	29.28	1.23	0
5	28.71	28.29	1.46	5
10	20.72	20.07	3.14	10
15	13.02	11.57	11.14	15
20	12.24	10.61	13.36	20
25	11.79	10.43	11.53	25
30	11.69	10.33	11.64	30

Table 3 summarizes the results in Figure 2 and introduces the percentage improvement in MLE. It is evident that as SNR increases, the proposed technique outperforms the standard DV-Hop. MLE improvement reaches 13.36% at SNR of 15 dB.

8.2 Impact of number of sensors on mean localization error (MLE)

Figure 3 presents the results of changing the number of sensors with respect to the total number of anchors. It depicts MLE at SNR of $15dB$ for DV-Hop and DV-HOP-VVS-HCO. Moreover, it presents how the MLE improved via the use of DV-HOP-VVS-HCO as compared to DV-Hop. It is evident that both techniques are affected by increasing number of sensors to number of anchors. However, DV-HOP-VVS-HCO is more stable with lower sensitivity to noise. Its superiority becomes more noticeable at higher nodes to anchors count ratio

(NACR). As NACR reach 10, the MLE improvement reaches about 23%. However, it is expected that the MLE will decrease as the NACR increase, the wireless channel and the existence of RF noise affects the behavior. The wireless channel impairments cause more error accumulation as the number of node increases. Moreover, if the received signal by a node falls below its sensitivity due to channel attenuation, it may be reported by the transceiver as noise which causes a node to disconnect from the network and cause more localization errors.

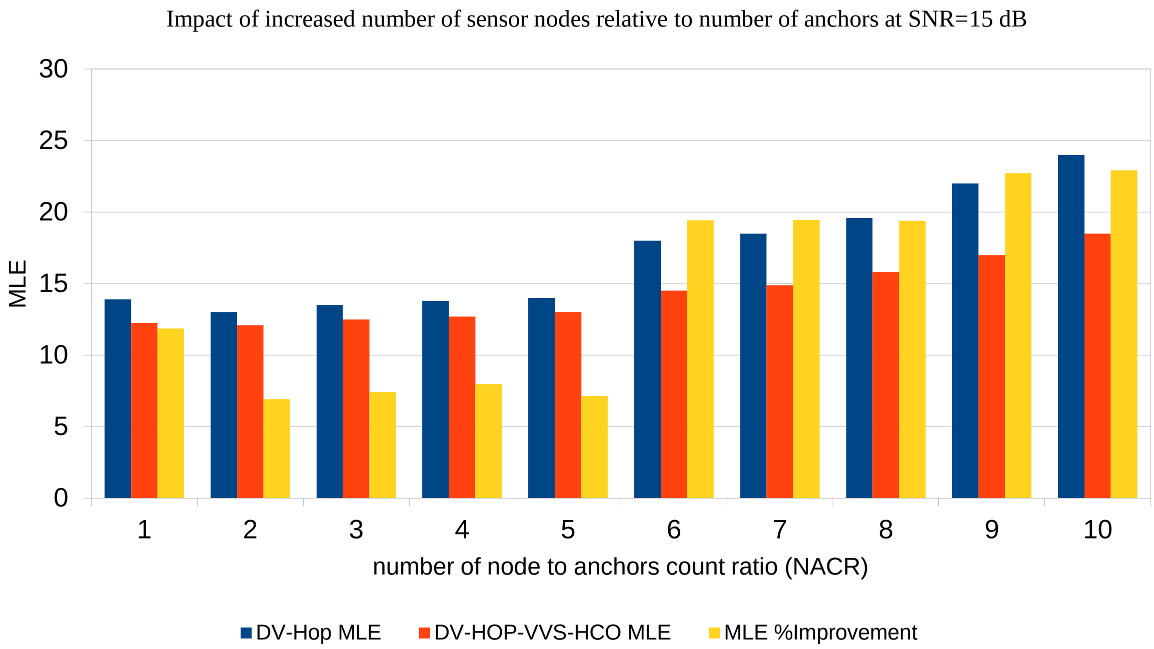

Figure 3: Impact of increased number of sensors relative to number of anchors

Most of the studies presented in table 1 test the localization method performance is estimated without considering the wireless channel impairments, the channel noise, and the nodes and anchors' transceiver sensitivities. Due to the nodes becoming nearer as NACR increases, they can connect to each other and to the anchors successfully. So, most of the nodes become connected to the network and hence can be localized and this results in a decrease in the NACR. This scenario is valid if no channel impairments exist. Hence the effect of wireless channel nature can impact the performance of a range free localization technique.

8.3 Discussion and Insights

The experimental results make significant observations. Optimizing the hop distance results in better localization accuracy that is less dependent on the tightly fixed hop-size assumptions adopted in classical DV-Hop. The proposed DV-HOP-VVS-HCO approach adaptation to noisy conditions is demonstrated where stable localization accuracy is maintained under changing the SNR. In addition, NACR suggests that the proposed method is more applicable for large-scale WSN implementations with low computation overhead. The developed model achieves a good trade-off between accuracy and efficiency and can be also a versatile solution for autonomous navigation, smart city, and IoT-based localization system.

However, the DV-HOP-VVS-HCO localization algorithm adds extra computational load to the original DV-Hop algorithm, as most of the optimized DV-Hop based localization techniques that are spotted in Table 1 [31-35], [37, 38], overcome most of their limitations. It proves its robustness against node density, random node distributions, different node to anchors count ratios, and wireless channel conditions. It still needs to be tested for moving nodes scenarios.

Future work could investigate real-world deployment and additional optimizations, such as the adoption of reinforcement learning-based for adaptive hop-size estimation, to improve localization robustness in severe environments. In addition to testing and adapting it to mobility scenarios. Moreover, the proposed DV-Hop-VVS-HCO can be compared to other developed range free localization techniques in the literature under the effect of different wireless channel models for different environments.

9. Conclusion

This paper proposed an improved localization scheme for WSN sensor nodes, where the DV-Hop range free localization scheme estimations are optimized for better location estimation of sensor nodes. The variable velocity strategy (VVS) and human conception optimization (HCO) techniques are combined within the DV-Hop to enhance its location estimations for the sensor nodes. The proposed technique is evaluated via building a wireless sensor network (WSN) using simulations. The WSN is constructed by randomizing the sensors and anchor's locations. Every node is assumed to be equipped with an RF transceiver with a predefined coverage range that is set at the beginning of the simulations, so that the nature of the wireless communication channel and its impact on estimation accuracy is exploited. The effect of noise on the wireless channel and on the localization, algorithms are included in the simulations. The experimental results show that the proposed DV-HOP-VVS-HCO outperforms the standard DV-Hop technique by about 11% to 13% at moderate SNR values. Changing the number of sensors also validates the more accurate proposed technique: It reduces the dependency on static assumptions, i.e., the algorithm is more adaptable to the sensor to anchors counts and of course the topology changes and randomness of node distributions. The results indicate that the proposed DV-HOP-VVS-HCO model can withstand the increase in the node populations and density in the existence of RF signal attenuation and wireless channel noise. While the DV-Hop' means localization error (MLE) reaches about 25 m at nodes to anchors count ratio (NACR) of 10, the DV-HOP-VVS-HCO 'MLE reaches about 17m with percentage improvement of about 23%. The DV-HOP-VVS-HCO is an excellent candidate for applications when accurate and robust localization (e.g., autonomous navigation and IoT based smart city system) is required especially at moderate values of NACR. It proves it acceptable performance and accuracy in realistic WSNs as common wireless transmission impairments are modeled in the simulations.

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