SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V11I9P125

Volume 11 Issue 9, 274-283, September 2024

Original Article

Investigating the Impact of Kalman Filter to Minimize the Localization Error in Wireless Sensor Networks

Srivani Reddy[1], A. Kamala Kumari[2], Ch. Sita Kumari[3]

[1,2]*Instrument Technology, Andhra University College of Engineering, Andhra Pradesh, India.*
[3]*CSE, Gayatri Vidya Parishad College of Engineering(A), Andhra Pradesh, India.*

[1]*Corresponding Author : rsrivani5@gmail.com*

Received: 12 July 2024 Revised: 14 August 2024 Accepted: 11 September 2024 Published: 28 September 2024

Abstract - *Wireless Sensor Networks (WSN) comprise sensors that are spatially distributed, collecting information and reporting the data back to the control module. Knowing the sensor (node) positions is necessary for most applications, and the sensor positions are estimated using Localization algorithms. This paper proposes a strategy that uses the Kalman Filter (KF) approach with the proposed range free centroid localization algorithm to increase the accuracy of any unknown node's predicted position in a network. The parameters, namely nodes, network size, communication range, and deployment of the network, have been varied, and the performance of the proposed system comprising the range free centroid localization algorithm with Kalman filter is studied. Combining the Kalman filter with the proposed range free centroid localization algorithm enhances the methodology and increases the success rate in the presence of measurement errors. The simulation results demonstrate that the suggested technique enhances the location accuracy of unknown nodes.*

Keywords - *Centroid, Kalman filter, Localization, Range-free, Wireless Sensor Networks.*

1. Introduction

Wireless Sensor Networks (WSN) [1] are used for a variety of industrial, scientific, and naval applications, including system monitoring, weather recording, natural disaster prediction, and medical treatment in hospitals. Node position is critical for Wireless Sensor Networks (WSN) applications; hence localization is required.

Localization techniques are used to precisely position unidentified sensor nodes inside the network using anchor nodes. Anchor nodes are those that have prior information or positions, which can be gained by using a Global Positioning System (GPS) or establishing nodes with known coordinates. Unknown nodes, also known as non-anchor nodes, are nodes that do not know their location and must have their coordinates approximated using a sensor network localization technique.

The existing localization strategies [2-5, 13, 15, 16] are broadly classified into two types: range-based and range-free localization algorithms. Range-based systems [6] precisely quantify the distance or angle data between sensor nodes before determining the position via trilateration or triangulation methods. Range-based systems include Time of Arrival (TOA), Angle of Arrival (AOA), Time Difference of Arrival (TDOA), and Received Signal Strength Indicator (RSSI). The Global Positioning System (GPS) is a widely used range-based system that employs Time Difference of Arrival (TDOA) or Time of Arrival (TOA) methodologies. Nevertheless, GPS devices are unsuitable for indoor or underwater devices. The Global System for Mobile (GSM) communications, which uses Received Signal Strength Indication (RSSI) and Angle of Arrival (AOA) techniques, is an alternative to the Global Positioning System. The GPS and GSM algorithms are complex and sophisticated technologies. The Ultra-Wide Band (UWB) is an alternative range-based method that can be used to predict flight time with high accuracy. Although range-based approaches are less expensive, they are affected by multipath fading, noise, and environmental fluctuations.

Range-free localization approaches with no limitations [7, 8, 13] make use of connection information between nodes. Initially, unknown nodes gather knowledge about their connections and the locations of anchor nodes. They then utilize this information to calculate their own positions with the assistance of anchor nodes. Approximate Point in Triangle (APIT), Distance Vector Hop (DV-hop), Multi-hop, Centroid, and Gradient are examples of non-range-specific localization techniques. Range-free systems are cost-effective and resistant to environmental changes. When selecting a localization method, it is critical to strike a balance between accuracy, cost, and dependability in various contexts. Range-based approaches are more exact but require specialized equipment and are often influenced by factors like as noise and obstacles. This makes them perfect for applications requiring great accuracy, such as GPS, 5G networks, or tracking cars and drones. In contrast, range-free methods are much more affordable and energy-efficient. They do not require extra hardware, making them a good choice for large-scale, low-power applications like environmental monitoring or tracking devices in smart homes. However, this simplicity comes with lower accuracy. Range-free methods are more likely to experience errors from issues like connectivity, signal interference, and node placement. In complex environments, signal strength can vary a lot, making it hard to create a reliable localization method. This makes range-free techniques less effective for dynamic or precise applications.

To address these issues in range free localization methods, optimized techniques that combine these approaches with advanced algorithms to enhance accuracy and precision have been developed. Advanced algorithms such as the Kalman filter, particle filter, graph-based SLAM (Simultaneous Localization and Mapping), machine learning models, and probabilistic techniques can significantly improve the overall performance of localization systems.

Optimized localization techniques offer substantial improvements in accuracy, efficiency, robustness, and adaptability. This makes them essential for applications requiring real-time, precise localization, such as autonomous driving, robotics, augmented reality, and other dynamic systems. In this research, the Kalman filter is applied to improve the accuracy of range-free localization methods by filtering out noise from location estimates, ultimately leading to more reliable and precise positioning.

A comprehensive evaluation was conducted on a wide range of research articles, focusing on various algorithms designed for diverse objectives such as accuracy, cost, and scalability. According to current research, a typical range-free localization technique requires at least three adjacent anchor nodes to establish the location of an unknown node. Bulusu [9] was the first to introduce the centroid localization technique. The centroid of neighboring anchors within the communication range represents the unknown node's approximate position.

There are M anchor nodes which are placed at known positions $An_1(Xa_1, Ya_1)$, $An_2(Xa_2, Ya_2)$,… Anm (Xam,Yam), and an Unknown node whose position is UN(x,y). All these nodes have the same communication range and spherical radio propagation. Among these M anchor nodes, N anchor nodes (An_1, An_2……Ann) are within the range of the Unknown Node (UN). UN localizes itself as the centroid of these N anchors, as shown in Figure 1. The unknown node calculates its location using the centroid formula.

$$UN(\mathrm{X,Y}) = \left(\frac{\mathrm{X_{a1}+X_{a2}+\cdots+X_{an}}}{\mathrm{N}}, \frac{\mathrm{Y_{a1}+Y_{a2}+\cdots+Y_{an}}}{\mathrm{N}}\right) \quad (1)$$

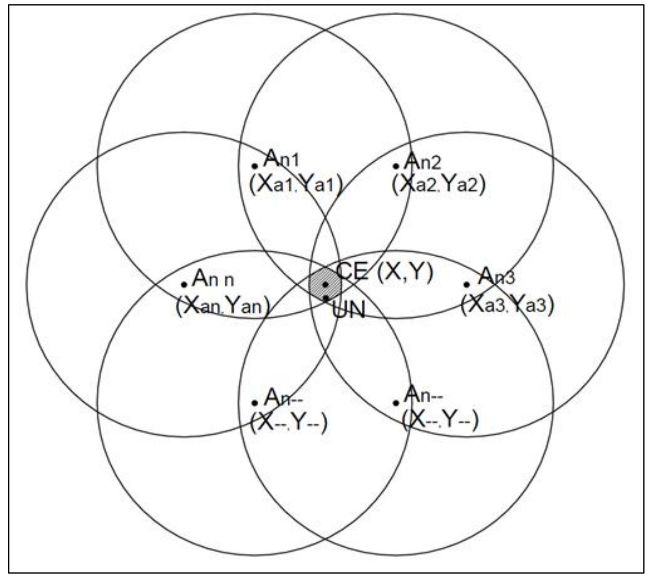

Fig. 1 Centroid localization

An1, An2 , An3… Ann are Anchor neighbor nodes
UN – Un Known Node
CE – Centroid
(X, Y) – Co-ordinates of the Centroid

Linqing Gui et al. [10] suggested a number of ideas for mid perpendicular localization. This set of criteria employs the intersection points of perpendicular lines to determine the approximate location of the unknown nodes. The investigation focused on two cases. The first sample had an unknown node with at least three neighboring anchor nodes, but the second contained more than three anchor nodes. In the first scenario, let $A_{n1}(Xa_1, Ya_1)$, $A_{n2}(X_{a2}, Ya_2)$, and $A_{n3}(X_{a3}, Y_{a3})$ be the coordinates of at least three neighbouring anchors that form a triangle. If the triangle is an acute perspective triangle, then the expected function is the intersection factor of mid perpendiculars. If the triangle is right-angled or obtuse, the predicted location is the median of its longest side. In the second scenario, if there are more than three neighbouring anchor nodes, they select three anchors in such a way that the area of overlap between the three nodes is as small as possible.

The author have presented techniques for localizing the orthocenter and circumcenter. The orthocenter is the point where the elevations of a triangle coincide. The circumcenter of a triangle is the point at which the perpendicular bisectors of its edges meet. These approaches require a minimum of three neighboring nodes that are within communication range. If there are at least 3 neighbouring anchor nodes, the orthocenter and circumcenter can be seen and considered as the approximate position of the unknown node, respectively. If there are more than 3 anchor nodes, all possible combinations of three nodes are found, and triangles are formed. Next, the orthocenter and circumcenter of each triangle are determined, and the median of these points is regarded as the anticipated function of the unknown node. Furthermore, they investigated the effects of localization errors by varying network length, communication range, and the number of nodes. Another way is to estimate the area of an unidentified node using Kalman filtering. The Kalman filter [17, 18, 20-22, 26-28] minimizes error by using all available data and earlier knowledge about the system and measurement devices to provide an estimate of the node coordinates. As a result, the Kalman filtering technique can be utilized to produce a more reliable and precise estimate of an unknown node's location, even in a noisy system.

Yunfei et al. [12] suggested a triangular centroid localization algorithm based on Kalman filters. The Received Signal Strength Indicator (RSSI) values are kept in an array. The triangular centroid technique is employed to calculate the proximity of the first-class. The Kalman filter is utilised to determine the optimal distance. The Kalman filter, implemented using the triangular centroid approach, effectively mitigates the issue of signal interference in Wi-Fi networks. This results in reduced noise and improved accuracy in determining the location of Wi-Fi signals. The author attains a low cost and excellent positional accuracy by utilising the Kalman filter.

The introduction of target monitoring in Wireless Sensor Networks (WSN) was initially presented by Ashwin et al. [19], who utilised a constant value Kalman filter approach. The authors claim that this method exhibits equivalent performance in both standalone and information-fusion modes for goal tracking. This finding is significant because it demonstrates that the reliable Kalman filter effectively manages the trade-off between advantages and the difficulty of getting filter data, thus avoiding potential issues in the system.

Abdelhady et al. [23] recommended utilizing the Kalman Filter (KF) technique to assess sensor node proximity. The suggested method was evaluated by comparing it with two training versions of the Flexible Optimal Kalman Filtering (FOKF) algorithm. The evaluation focused on analyzing the impact of the new method on anchor node density, movement velocity, and irregular radio transmission. Concerning obstacles in recalling past events, the consumption of electricity, and the accuracy of determining a certain position.

Kumar, B. S. et. al. [24] scrutinized structures by inputting values to achieve desired outcomes using the Ad hoc On-Demand Distance Vector (AODV) immediate routing protocol. The methodology is explained in the related work, accompanied by accessible simulation methods for outcomes. The planned execution involves simulation module deployment within a real-time environment to produce valid, verifiable and executable results. Kumar, B. S., et al. [25] used soft computing models to estimate the appropriate alpha, beta, and gamma values for the Prophet routing protocol in delay tolerant networks. This forecast is based on data simulated with the ONE simulator. Prediction is based on a dataset simulated using the ONE simulator.

In this work, to improve accuracy, the proposed Range Free Centroid Localization algorithm is combined with the Kalman filter. The purpose of this research is to evaluate the effectiveness and practicality of the proposed range-free centroid localization technique [9, 10] with and without the Kalman filter. Verify the influence of the various parameters such as transmission range, node deployment models [14, 15], simulation area, number of nodes, and so on, the proposed range-free centroid localization algorithm with Kalman filter.

2. Kalman Filter

The Kalman Filter is an advanced, recursive technique for determining the state of a dynamic system using noisy observations. It predicts the system's next state and updates this prediction using a weighted average of the estimate and new data, with the weights determined by the uncertainties in both. Its recursive nature enables real-time processing, making it ideal for applications requiring timely, accurate state estimation, such as control systems, navigation, and signal processing. The filter is widely valued for its simplicity and robustness.

Mathematical formulation:

$$X_t = AX_{t-1} + BU_t + W_t \tag{2}$$

$$Z_t = HX_t + V_t \tag{3}$$

X_t = State Vector at time T
A = State Transition Matrix.
B = Control Input Matrix
U_t = Control Vector
W_t = Process Noise
Z_t = Measurement Vector
H = Measurement Matrix
V_t = measurement noise.

2.1. Integration of the Kalman Filter into the Proposed Range-Free Centroid Localization Method

The Kalman Filter is a highly significant and commonly used estimate method. The Kalman filter is employed in radar systems, as well as in area and navigation systems, for goal tracking purposes. The Kalman filter can estimate the present state by taking into account the known predicted value of the previous state and the measured value of the present state. The suggested centroid localization approach based on Kalman clearing out can substantially enhance position accuracy by filtering noise. Kalman filters are typically initialized by guessing their initial state. The starting state estimations are X_0 and Y_0, and they quickly converge to the point where the influence of the first guess is negligible. The state update equation for the Kalman Filter is presented in Figure 2. The functioning of the Kalman filter is divided into two parts: prediction and update. In the prediction phase, the location coordinates at iteration (t) are predicted using the ideal position at iteration (t -1) in the update phase.

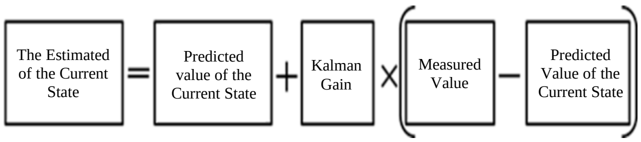

Fig. 2 State update equation for Kalman filter

The correction is updated again to reach the optimal value at iteration (t). This process is repeated continuously till the last iteration. Here, the Kalman gain (α) is set to 0.5. The Kalman gain adjustment depends on the precision of measurement. For high-precision measurement, a high value of gain is chosen. The iteration equation for the Kalman filter is as follows:

$$X_t = X_{t-1} + \alpha\,(MV_X - X_{t-1}) \quad (4)$$

$$Y_t = Y_{t-1} + \alpha\,(MV_Y - Y_{t-1}) \quad (5)$$

X_t = Current Estimate of the X- co-ordinate value
X_{t-1} = Predicted value of X co-ordinate (previous estimate)
Y_t = Current Estimate of the Y- co-ordinate value
Y_{t-1} = Predicted value of Y co-ordinate (previous estimate)
α = Kalman Gain
MV_X = value of X co-ordinate by applying the proposed range free centroid method
MV_y = value of Y co-ordinate by applying the proposed range free centroid method

3. Methodology

In order to study the dynamic behaviour of a system under controlled settings, an artificial environment has been developed in which relevant information and data could be generated. The schematic diagram illustrating the research methodology is depicted in Figure 3. The application of the proposed range-free centroid localization algorithm results in an unacceptable level of localization error. By integrating the Kalman filter with this algorithm, the estimated position of unknown nodes is optimized.

This research effort focuses on integrating the Kalman filter with range-free localization algorithms to improve accuracy and reduce localization error. The experiments are simulated using the MATLAB platform, and the simulations are performed in different simulation areas and communication ranges for different values of number of nodes, and mode of deployment (either Random or Uniform). Uniform distribution has uniform sensor node density throughout the network, and Random deployment has sensor nodes placed randomly in the given Network area. The simulation parameters are shown in Table 1. In Wireless Sensor Networks (WSNs), localization algorithm accuracy is crucial to system performance. Several performance indicators are utilized to evaluate and quantify localization inaccuracy. The most widely utilized performance measurements [29] include average localization error, mean absolute error, mean squared error, root mean squared error, and relative errors. The average localization error is an important parameter for evaluating the accuracy of localization algorithms in WSNs. It measures the average distance between true and estimated positions.

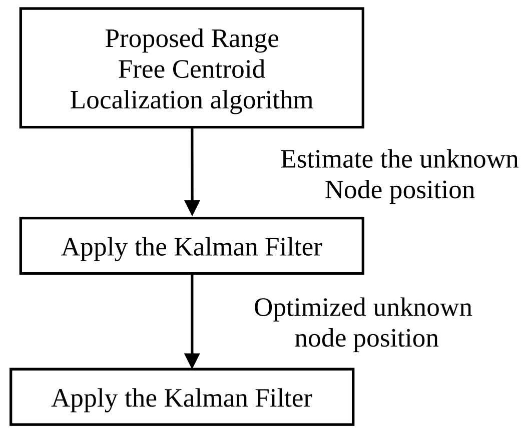

Fig. 3 Schematic of research methodology

$$\mathrm{ALE} = \frac{1}{M}\sum_{i=1}^{M}\sqrt{(X_{tp} - X_{iep})^2 + (Y_{tp} - Y_{iep})^2} \quad (6)$$

M = Number of estimated positions.
(X_{tp}, Y_{tp}) = True Position
(X_{iep}, Y_{iep}) = Estimated Position

Mean Absolute Error (MAE): This statistic calculates the average difference between expected and actual values by calculating the absolute value of their deviations, adding them together, and dividing by the number of samples.

The Mean Squared Error (MSE) is computed by averaging the squared differences between expected and observed values. It is determined by adding the squared differences and dividing by the total number of data points.

Root Mean Square Error (RMSE) is the square root of MSE and is widely used to evaluate model performance due to its sensitivity to larger errors.

Relative Error: This metric compares the error in an estimate or measurement to the actual value, providing a ratio that highlights the error's size relative to the true value, often stated as a percentage.

$$\text{Relative error} = \frac{|\text{Estimated Value-Actual Value}|}{|\text{Actueal Value}|} \quad (7)$$

Table 1. Simulation scenario parameters

Simulation Parameter	Value
Network simulation area	80 x 80, 100 x 100, 120 x 120 and 140 x 140
Number of anchor nodes	16, 20, 25 and 30
Radio range	15, 18, 20 and 23
Radio propagation model	Ideal, no path loss, no interference
True location of the unknown node	(50,50)
Deployment model	Random and Uniform
Number of iterations	5000

4. Experimental Results and Evaluation

The usefulness and feasibility of the proposed range-free centroid localization algorithms, with and without the Kalman filter, have been verified by conducting experiments several times to identify the factors affecting the localization algorithm.

Range-free localization algorithms utilize two primary pieces of information: anchor node positions and connectivity between nodes. Anchor nodes are placed throughout the simulation area with known coordinates and periodically broadcast signals. An unknown node within the area, connected to at least three anchor nodes, can estimate its location using these signals.

The proposed range-free centroid localization algorithm generates a rough approximation by computing the centroid of anchor nodes within its communication range. However, this method is susceptible to errors due to signal interference and propagation issues. To mitigate these challenges and enhance localization accuracy, a Kalman filter can be employed. The Kalman filter continuously refines the estimated position by incorporating new measurements from the proposed range-free centroid algorithm. It effectively smooths out abrupt changes caused by noise, environmental conditions, or the varying distribution of anchor nodes, which changes with each iteration. This dynamic update process significantly improves the accuracy and stability of the estimated location over time.

4.1. Simulation Results of Proposed Range-Free Centroid Localization Algorithms with and without the Kalman Filter

The nodes are deployed in a simulated area, and the unknown node is placed at an assumed location in the given simulated area. The average localization error has been calculated by a proposed range-free centroid localization algorithm [11] with and without the Kalman filter based on connectivity information. The accuracy of these algorithms is quantized with respect to communication range.

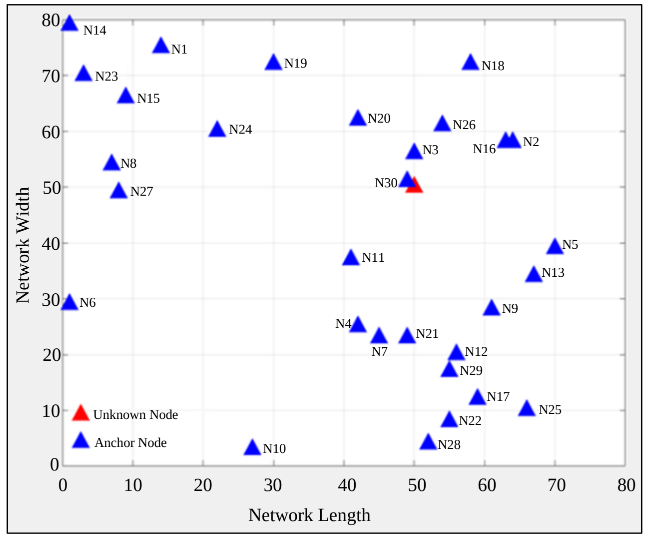

Fig. 4(a) Randomly deployed nodes within area 80 x 80m²

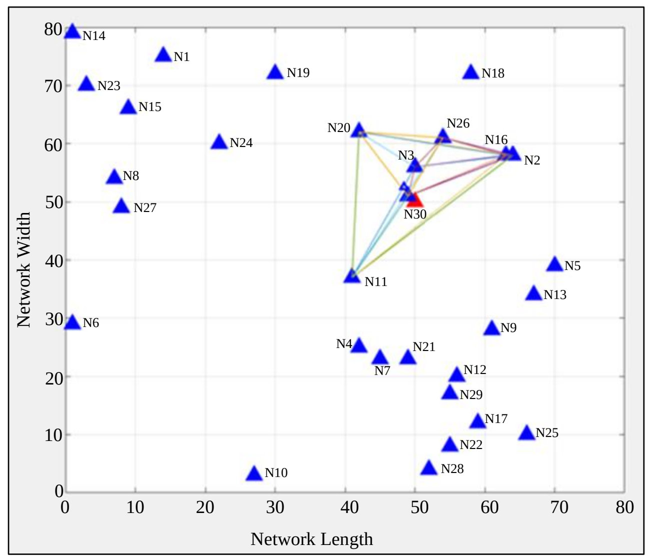

Fig. 4(b) Localization using the proposed method on the randomly deployed nodes within the proposed area

The metric for evaluating the performance is localization error with respect to communication range, which is defined as the distance between the true and estimated positions. The experiment region is a two-dimensional square area of $80 \times 80m^2$, with an 18-meter communication range. 30 anchor nodes are spread within the area, and the unknown node position is fixed, as shown in Figure 4(a). The proposed range-free centroid localization algorithm is applied in Figure 4(b). Figure 5 depicts the graphical output of the proposed range-free centroid localization techniques, both with and without the Kalman filter. Figure 5(c) demonstrates the effect of the Kalman filter on localization error in random deployment with varying numbers of interactions. Figures 5(a) and 5(b) shows a comparison of the actual positions and position estimations derived from measured data before and after using the Kalman filter.

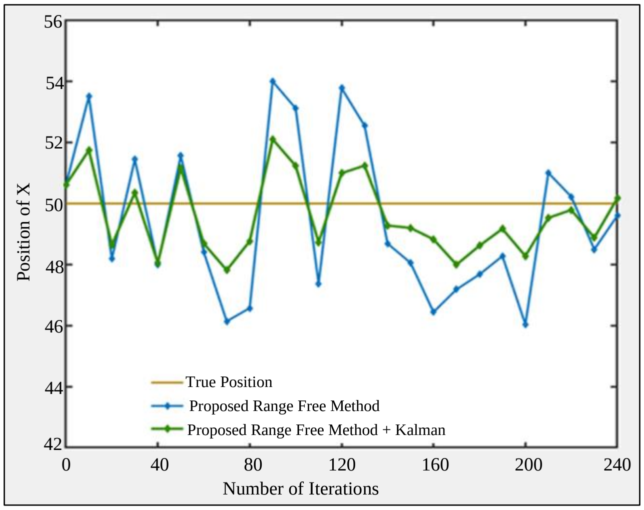

Fig. 5(a) Impact of the Kalman filter on the position of X in random deployment with varying number of iterations

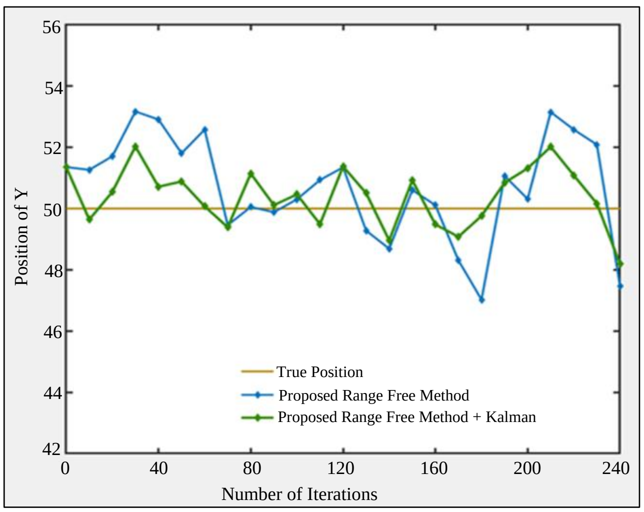

Fig. 5(b) Impact of the Kalman filter on the position of Y in random deployment with varying numbers of iterations

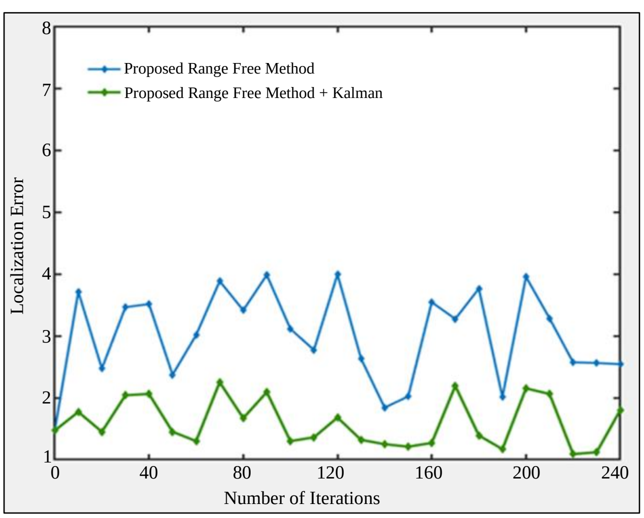

Fig. 5(c) Impact of the Kalman filter on the localization error in random deployment with varying number of iterations

Figure 5(c) depicts the size of the estimated error at various iterations for position estimates produced from measured data using the proposed range-free centroid localization techniques against position estimates after applying the Kalman filter. With the Kalman filter, for every iteration, the current estimates obtained are dependent on the Values (MV_X, MV_y) that are obtained from the application of the proposed range-free centroid localization algorithm and the previous estimates (X_{t-1}, Y_{t-1}), as shown in Equation (4) and Equation (5).

The localization error, which is the Euclidean distance between the current estimated position and its actual position, varies at every iteration. A significant reduction in the error that occurred can be observed with the application of the Kalman filter. The Kalman filter improves the algorithm's location accuracy by 40–50%. While the magnitude of the error is reduced by applying the number of iterations seems to have no influence on the magnitude of the error since there is no trend in the magnitude of the error with the increase in number of iterations between the estimated and actual positions, varies with each iteration. The adoption of a Kalman filter has the potential to significantly reduce error. Table 2 shows some of the sample observations based on simulation findings.

4.1.1. Tenth Iteration

Average Localization Error in the application of proposed range-free centroid localization algorithms without a Kalman filter.

$(MV_{X10}, MV_{y10}) = (53.5,51.26)$ meters.

Average Localization Error

$$= \sqrt{\left(X_{tp} - MV_{X10}\right)^2 + \left(Y_{tp} - MV_{Y10}\right)^2}$$

$$= \sqrt{(50 - 53.5)^2 + (50 - 51.26)^2} = 3.72 \text{ m}$$

Average Localization Error in the application of proposed range-free centroid localization algorithms with a Kalman filter.

$(X_9, Y_9) = (49.97, 48.02)$ meters

$X_{10} = X_9 + \alpha\,(MV_{X10} - X_9)$

$X_{10} = 49.97+0.5\,(53.5-49.97) = 51.74$ meters

$Y_{10} = Y_9 + \alpha\,(MV_{Y10} - Y_9)$

$Y_{10} = 48.02+0.5\,(51.26-48.02) = 49.64$ meters

Average Localization Error without Kalman Filter

$$= \sqrt{\left(X_{tp} - X_{10}\right)^2 + \left(Y_{tp} - Y_{10}\right)^2}$$

$$= \sqrt{(50 - 51.74)^2 + (50 - 49.64)^2} = 1.78 \text{ meters}$$

Table 2. Sample observations from the simulation

Iteration No	True Position in Meters		Estimated Position in Meters				Localization Error in Meters	
			Without Kalman Filter		With Kalman Filter		Without Kalman Filter	With Kalman Filter
	X	Y	MV_X	MV_Y	X_t	Y_t		
10	50	50	53.5	51.26	51.74	49.64	3.72	1.78
30	50	50	51.44	53.16	50.35	52.02	3.47	2.05
50	50	50	51.56	51.8	51.16	50.88	2.38	1.46
70	50	50	46.15	49.46	47.82	49.39	3.89	2.26
90	50	50	53.99	49.88	52.1	50.11	3.99	2.1
110	50	50	47.38	50.93	48.73	49.49	2.78	1.37

$$\textbf{Percentage of Relative error} = \frac{\textbf{Error without kalman} - \textbf{Error with kalman}}{\textbf{Error without kalman}} \textbf{x100}$$

$$\%\ \textbf{Relative error} = \frac{\mathbf{3.72 - 1.78}}{\mathbf{3.72}} \textbf{x100} = \mathbf{52.15\%}$$

The relative error between the proposed range-free centroid localization algorithm with and without the Kalman filter is 52.15%, indicating that the Kalman filter improves localization accuracy by 52.15% compared to the algorithm without it.

4.2. The Impact of Different Parameters on Proposed Range-Free Centroid Localization Algorithms with Kalman Filter

Experiments have been carried out to validate the parameters that influence the proposed range-free centroid localization methods using Kalman filters in a variety of scenarios. In each scenario, one parameter is varied while the others are kept constant, and the simulation runs up to 5000 times with different geographic distributions of anchors. The localization error can be determined for each distribution of anchor nodes, and the average value can be evaluated. The simulation findings show a 95% likelihood of dependability. To determine the effect of the localization algorithm, the following parameters are taken into account.

4.2.1. The Impact of Simulation Area, i.e. Network Size

To investigate the effect of network size for different deployment models and communication ranges on proposed range-free centroid localization algorithms with Kalman filter under the conditions: the number of nodes is kept constant at 25, communication ranges vary from 15m to 23m, network size varies from 80 X 80 m^2 to 140 X 140 m^2, and nodes are distributed randomly and uniformly. Figure 6 shows the simulation findings, which have a 95% chance of reliability.

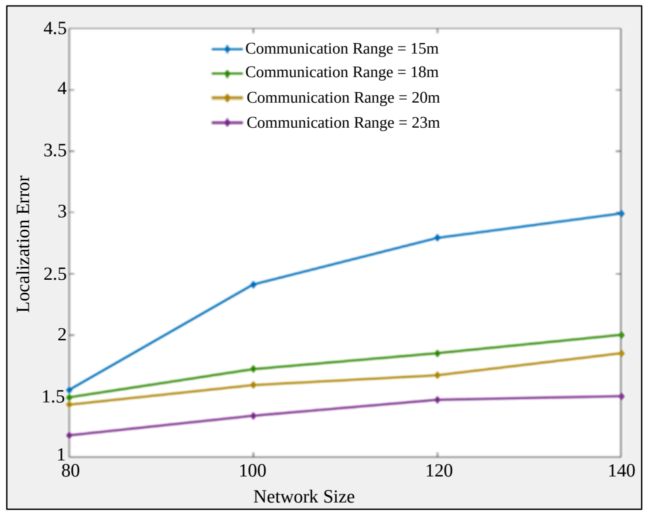

Fig. 6(a) 25 nodes are randomly placed, varying the network sizes for different communication ranges

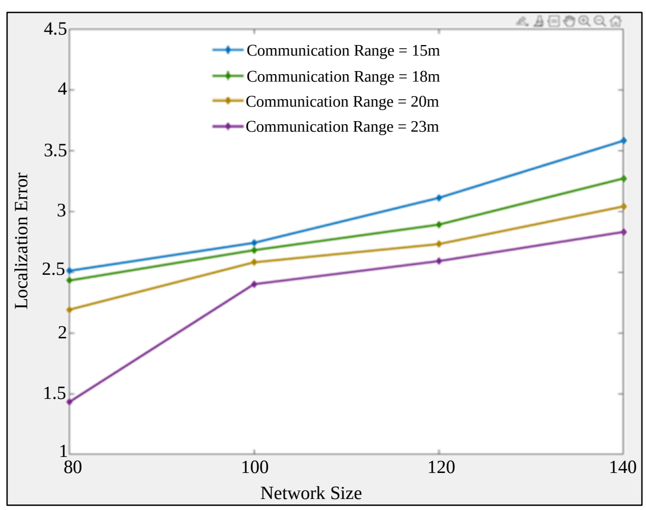

Fig. 6(b) 25 nodes are uniformly placed, varying the network sizes for different communication ranges

4.2.2. The Impact of Number of Nodes.

The network size was kept constant at 120 X 120 m^2, communication ranges varied from 15m to 23m, the number of nodes varied from 16 to 30, and nodes were distributed randomly and uniformly to investigate the effect of a number of nodes for different deployment models. Communication ranges on proposed range-free centroid localization algorithms with Kalman filter. Figure 7 shows the simulation results, which have a 95% chance of reliability.

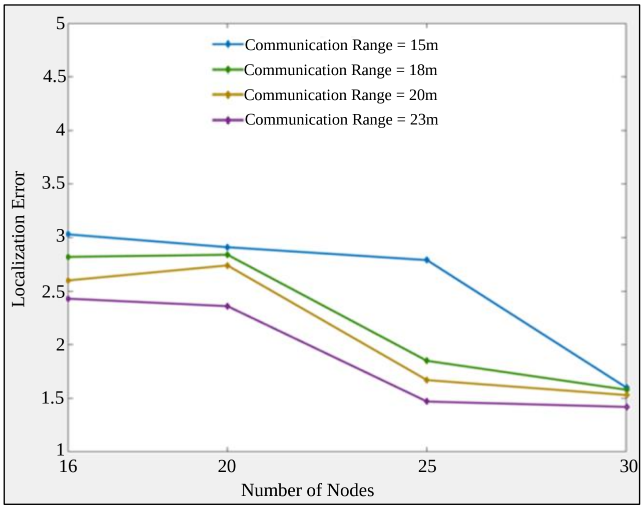

Fig. 7(a) 120 x 120 m^2 network size, vary the communication range for different numbers of nodes placed in Random deployment

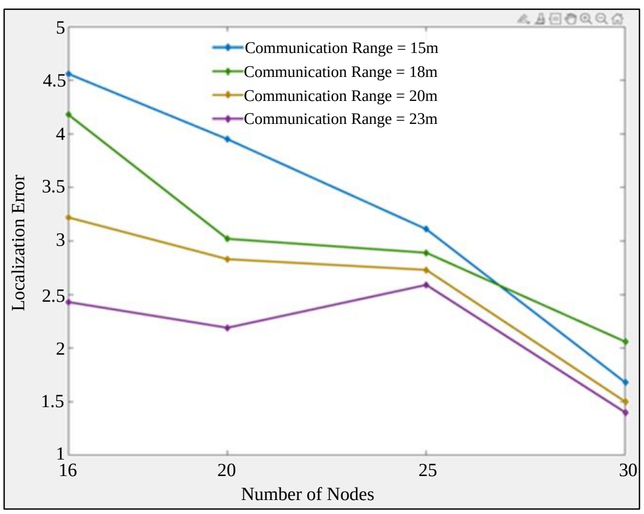

Fig. 7(b) 120 x 120 m^2 network size varies the communication range for different numbers of nodes placed in Uniform deployment

Observations of graphs in Figures 6(a), 6(b), 7(a) and 7(b**)** are as follows:

- By increasing the number of nodes, localization error becomes reduced because the unknown nodes have more precise position reference information.
- By increasing the range, the overlap area of nodes increases, the localization regions become finer, and hence, the location estimate accuracy improves.
- By increasing the size of the network, the localization error also increases because network size increases, the coverage area is reduced then the error increases.
- The localization error is minimal in random deployment compared to uniform deployment. If the number of nodes in the simulated area decreases, the communication holes occur more in uniform deployment compared to random deployment.

5. Concusion

The Kalman filter is one of the most effective approaches for localizing using noisy measurements in a wireless sensor network. In this study, the Kalman filter approach was applied to the proposed range-free centroid Localization algorithm to improve localization accuracy with respect to communication range.

A comparison of proposed range-free centroid localization techniques with and without the Kalman filter has also been conducted. The method incorporated a Kalman filter, which can enhance positioning accuracy with fewer iterations while also preventing system faults. Simulation results suggest that the proposed range-free centroid localization technique with the Kalman filter improves accuracy.

Localization error reduces as the number of nodes and communication range rises. The localization inaccuracy grows in proportion to the network size. In future studies, this technique will be applied to additional algorithms to improve QOS. The future of localization in WSNs will be more accurate, energy-efficient, scalable, and adaptive. A significant trend is the increasing usage of hybrid procedures that integrate different localization techniques. These approaches maximize each technique's strengths, boosting accuracy, robustness, and energy efficiency, making them appropriate for a wide range of applications in a variety of scenarios.

References

[1] Mohammed Sulaiman BenSaleh et al., "Wireless Sensor Network Design Methodologies: A Survey," *Journal of Sensors*, vol. 2020, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[2] C. Balasubramanian, M. Maragatharajan, and S.P. Balakannan, "A Range Based and Range Free Localization in Wireless Sensor Network," *International Journal of Recent Technology and Engineering*, vol. 8, no. 4S2, pp. 699-705, 2019. [CrossRef] [Publisher Link]

[3] Shivakumar Kagi, and Basavaraj S. Mathapati, "Localization in Wireless Sensor Networks: A Compact Review on State-of-the-Art models," *6th International Conference on Inventive Computation Technologies (ICICT)*, Coimbatore, India, pp. 5-12, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[4] S. Sivasakthiselvan, and V. Nagarajan, "Localization Techniques of Wireless Sensor Networks: A Review," *International Conference on Communication and Signal Processing (ICCSP)*, Chennai, India, pp. 1643-1648, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[5] Nabil Ali Alrajeh, Maryam Bashir, and Bilal Shams, "Localization Techniques in Wireless Sensor Networks," *International Journal of Distributed Sensor Networks*, vol. 9, no. 6, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[6] Fatiha Mekelleche, and Hafid Haffaf, "Classification and Comparison of Range-Based Localization Techniques in Wireless Sensor Networks," *Journal of Communications*, vol. 12, no. 4, pp. 221-227, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[7] Santar Pal Singh, and S.C. Sharma, "Range Free Localization Techniques in Wireless Sensor Networks: A Review," *Procedia Computer Science*, vol. 57, pp. 7-16, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[8] R. Khadim, M. Erritali, and A. Maaden, "Range-Free Localization Schemes for Wireless Sensor Networks," *TELKOMNIKA Indonesian Journal of Electrical Engineering*, vol. 16, no. 2, pp. 323-332, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[9] N. Bulusu, J. Heidemann, and D. Estrin, "GPS-Less Low-Cost Outdoor Localization for Very Small Devices", *IEEE Personal Communications*, vol. 7, no. 5, pp. 28-34, 2000. [CrossRef] [Google Scholar] [Publisher Link]

[10] Linqing Gui et al., "An Adaptive Range-Free Localization Protocol in Wireless Sensor Networks," *International Journal of Ad Hoc and Ubiquitous Computing*, vol. 15, no. 1-3, pp. 38-56, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[11] Jun Tian et al., "A Centroid Localization Algorithm for Wireless Sensor Networks Based on Finite Element Method," *IEEE 8th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, Chongqing, China, pp. 139-143, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[12] Yunfei Suo et al., "A Triangular Centroid Location Method Based on Kalman Filter," *Communications, Signal Processing, and Systems*, pp 448-458, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[13] Jyoti Kumari, Prabhat Kumar, and Sunil Kumar Singh, "Localization in Three Dimensional Wireless Sensor Networks: A Survey," *The Journal of Supercomputing*, vol. 75, pp. 5040-5083, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[14] Wint Yi Poe, and Jens B. Schmitt, "Node Deployment in Large Wireless Sensor Networks: Coverage, Energy Consumption, and Worst-Case Delay," *AINTEC '09: Proceedings of the 4th Asian Internet Engineering Conference*, pp. 77-84, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[15] Gayatri Devi, Rajeeb Sankar Bal, and Sasmita Manjari Nayak, "Node Deployment and Coverage in Wireless Sensor Network," *International Journal of Innovative Research in Advanced Engineering*, vol. 2, no. 1, pp. 139-145, 2015. [Google Scholar] [Publisher Link]

[16] Wenyan Liu et al., "Node Localization Algorithm for Wireless Sensor Networks Based on Static Anchor Node Location Selection Strategy," *Computer Communications*, vol. 192, pp. 289-298, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[17] Hakan Koyuncu, and Baki Koyuncu, "An Application of Kalman Filtering and Artificial Neural Network with K-NN Position Detection Technique," *Wireless Sensor Network*, vol. 9, no. 8, pp. 239-249, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[18] Ashwin Yadav et al., "A Constant Gain Kalman Filter Approach to Target Tracking in Wireless Sensor Networks," *IEEE 7th International Conference on Industrial and Information Systems (ICIIS)*, Chennai, India, pp. 1-7, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[19] Katerina Fronckova, and Pavel Prazak, "Possibilities of Using Kalman Filters in Indoor Localization," *Mathematics*, vol. 8, no. 9, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[20] Israr Ullah et al., "Ann Based Learning to Kalman Filter Algorithm for Indoor Environment Prediction in Smart Greenhouse", *IEEE Access*, vol. 8, pp. 159371-159388, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[21] Etikala Raja Vikram Reddy, and Sushil Thale, "A Novel Efficient Dual-Gate Mixed Dilated Convolution Network for Multi-Scale Pedestrian Detection," *Engineering, Technology & Applied Science Research*, vol. 13, no. 6, pp. 11973-11979, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[22] Grigore Cican et al., "Design, Manufacturing, and Testing Process of a Lab Scale Test Bench Hybrid Rocket Engine," *Engineering, Technology & Applied Science Research*, vol. 13, no. 6, pp. 12039-12046, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[23] Shraddha Panbude et al., "DFPC: Dynamic Fuzzy-based Primary User Aware Clustering for Cognitive Radio Wireless Sensor Networks," *Engineering, Technology & Applied Science Research*, vol. 13, no. 6, pp. 12058-12067, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[24] Bonu SatishKumar, "Soft Computing Approach to Enhance the Performance of AODV (Ad-Hoc on-Demand Distance Vector) Routing Protocol Using Active Route Time Out (ART) Parameter in MANETs," *Turkish Journal of Computer and Mathematics Education*, vol. 12, no. 2, pp. 3060-3068, 2021. [Google Scholar] [Publisher Link]

[25] Bonu Satish Kumar et al., "Performance Analysis of Prophet Routing Protocol in Delay Tolerant Network by Using Machine Learning Models," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 5, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[26] Yan Wang, Junhui Wan, and Jie Lai, "A Wireless Sensor Networks Positioning Method in NLOS Environment Based on TOA and Parallel Kalman Filter," *IEEE 19th International Conference on Communication Technology (ICCT)*, Xi'an, China, pp. 446-450, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[27] Yue Qi et al., "An Improved Kalman Filter for TOA Localization Using Maximum Correntropy Criterion," *28th Wireless and Optical Communications Conference (WOCC)*, Beijing, China, pp. 1-4, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[28] Abdelhady Naguib, "Localization in Mobile Sensor Networks Using Kalman Filter," *Indian Journal of Science and Technology*, vol. 15, no. 13, pp. 570-583, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[29] Salaheldin Edam et al., "Comparative Evaluation of Localization Range-Free Algorithms in Wireless Sensor Networks," *International Journal of Engineering, Science and Technology*, vol. 16, no. 2, pp. 1-10, 2024. [CrossRef] [Google Scholar] [Publisher Link]