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RSSI Based Localization System for Outdoor Wireless Sensor Networks

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Abstract—The most important components of Wireless Sensor Networks is localization. In situations when there are a lot of randomly placed sensor nodes, pinpointing the exact cause of any emerging problem becomes crucial. A contrasting analysis of the Free Space Propagation Model (FSPM) and the 2-Slope 2-Ray Model (2S2R), two popular propagation models, which have been modified to increase their efficiency using Recieved Signal Strength Indicator (RSSI) has been stated. To assess these models' performance in an area of forest while taking into account crucial variables as path loss, attenuation, environmental effects, path loss exponent, and accuracy. The FSPM, which is based on the inverse square law, makes the idealised assumption that there are no obstacles or reflections in the open space environment. This model is suitable for line-of-sight scenarios and open space deployments. It might not, however, adequately depict the effects of reflections and obstructions in actual surroundings. The 2S2R Model, on the other hand, takes both multi-path propagation and free space path loss into account. It provides a more accurate illustration of signal transmission by taking environmental reflections and obstructions into account. The 2S2R Model gives increased accuracy in reflective conditions and can offer insightful information for deployments in a forested area. This study aids in choosing an acceptable model for wireless communication in a forest environment and advances our understanding of propagation models. The comparison anal- ysis provides information on the precision, dependability, and applicability of the 2S2R Model and the FSPM, facilitating well- informed decisions for the deployment of wireless communicationsystems in forest areas.

Keywords—Wireless Sensor Networks (WSN), Recieved Signal Strength Indicator (RSSI), 2-Slope 2-Ray Model(2S2R), Local- ization, Free Space Propagation Model (FSPM).

I. Introduction

Wireless sensor networks (WSNs) consists of minor, in- expensive, low-power devices that are fitted with sensors to monitor physical and environmental conditions. Localization, which is one of the most difficult challenges in WSNs, is the procedure for mapping out the physical location of each sensor node in the network. Many WSN applications rely on localization, such as environmental monitoring, wildlife tracking, and asset tracking. There are two categories of localization techniques used in wsn: Range-based and Range- free. Range-based techniques are dependent on the measured angle or distance between nodes, whereas range-free methods rely solely on data transmission. Range-based approaches include Time of Arrival, Time Difference of Arrival, Angle of Arrival, and Received Signal Strength . Techniques like Centroid, DV-Hop, and Amorphous are examples of range-free techniques [1]. Outdoor WSNs face challenges such as signal attenuation which refers to loss of signal strength or power loss as it travels through a transmission medium, both wired like cables, optic fibres and wireless channels. It can occur due to a variety of factors including distance, interference, impedance mismatches, and medium properties. Multi-path propagation is the phenomenon in which a transmitted signal travels through multiple paths to the receiver due to reflections, diffraction, and scattering in the transmission medium. This phenomenon is common in wireless communications, particularly in urban areas, indoor environments, and obstacles. Interference is the presence of unwanted signals or noise that disrupts or degrades the quality of a desired signal. It occurs in all types of communication systems, including wireless, wired, and analogue., which can affect the accuracy and reliability of communication between sensor nodes. To keep track of any changes in the environmental conditions for wildlife or any natural disasters that affect forests, such as wildfires, a WSN with n numbers of randomly positioned sensor nodes has been considered. It is crucial to know the exact location of the sensor nodes. There are difficulties in the forest setting becauseto the thick vegetation, poor visibility, and uneven ground. Accuracy of localization may be impacted by these variables on radio signal transmission. These difficulties should be takeninto account while developing localization algorithms, and they should include defences against forest obstructions, multi-path fading, and signal attenuation. In order to overcome these difficulties, a variety of propagation models for outdoor WSNs have been created, some of which are as follows, the Friis transmission equation is a commonly used model, which considers the antenna gain, frequency, and distancebetween the sender and the recipient and is particularly useful in point-to-point communication scenarios. Another model is the Log-Distance Path Loss model, which is based on the inverse square law and assumes that the radio signal decays exponentially over distance. The 2-Ray Ground Reflection model, which takes into account the radio signal's ground- reflected and direct paths. This model is particularly useful in open environments such as agricultural fields [2], where there are few obstructions. Other models include the 1-slope Log-normal model, the 2-slope Log-normal model, and the Simplified 2-Slope, 2-Ray model [3]. We implemented twoof the above mentioned techniques to determine the location of wireless devices in an outdoor wireless sensor network, the 2S2R propagation model & the FSPM to estimate the physical location of the nodes based on the strength of the signal received at each beacon. The 2-ray 2-slope model takes into account the direct and reflected paths of the signal between two devices, as well as the effects of attenuation, signal strength decay over distance and other obstacles that arepart of the forest environment, whereas, the FSPM evaluates an obstacle-free direct line of sight and overlooks the influence of other environmental conditions. By measuring the RSSI of the signal at each anchor and using the propagation model, the distance between the devices can be estimated, which can then be used to determine the location of each device. Inchallenging outdoor settings such as forests with obstructions and multi-path fading, the 2S2R model outperforms the FSPM in determining the location of the target node.

II. Related Work

The process of locating sensor nodes in WSN is known as localization. In order to identify and resolve any accident or mishap, localization is crucial. Finding a sensor node's precise location is essential for pinpointing a problem's origin. Furthermore, determining the coordinates for a rocket or missile launch depends on the location. Localization becomes crucial because of the constant placement of sensor nodes. In the region of usage, the sensor nodes are dispersed both randomly and densely.

GPS is extremely expensive to use and uses a lot of energy, making it very impractical to use. As a result, theGPS module is only present in a limited number of nodes, known as anchor nodes and from these anchor nodes the placement of remaining sensor nodes are determined. The Range-free Localization algorithms are built on hop space, hop count data among beacon nodes and target nodes. Range- free localization are categorised on the basis of deployment scenarios. A criterion or decision rule called the Anchor Pair Condition Decision (APCD) is employed to determine whether anchor node pairings in the network are suitable for accurate localization. The geometric constraint based on the method LAPCD improves the accuracy by an average of 31.4% in comparison to DV-maxHop with respect to localization. [4].

Fuzzy logic is used to categorise the RSSI parameters of beacon nodes into specified domains and fuzzy inference rules for generating RSSI patterns. A trained neural network evaluates the deployment of target nodes using these patterns. To depict the predicted position of the sensor nodes, the average location of the beacons from RSSI patterns [5] isseparated by the proximity factor [6]. The technique utilising fuzzy logic and Neural Networks for localization in WSNare Fuzzy inference rules to create the RSSI patterns, and fuzzy logic is used to classify the RSSI values into predefined regions. The sensor nodes in the proposed Neuro-

Fuzzy based position recognition system is unknown, they are mobile, and are susceptible to retrieved with the support of nearby nodes. 95 percent of the final result was accurate [7].

A WSN localization strategy based on RSSI will help to minimise the impact of shadowing brought on between the obstructions that will be dispersed throughout the operation. This algorithm's main benefit is its ability to effectively coun- teract the effects of inaccurate distance calculations on node localization in a sensor network with obstructions. The systemwill use multilateration to estimate the location using a certainnumber of beacons on each subset, and then clusterization will be used to choose the location that is most likely to match the multilateration data [8]. One anchor node is all that is required in yet another technique for locating mobile submerged sen- sors, The bouncing method is used to calculate the separation between the anchor and the sensors co-ordinates which is aidedby multi- and trilateration techniques.Trilateration and multi- lateration help increase the bouncing technique's accuracy, which is 84.35% [9].

Ad-hoc Positioning, Robust Positioning, and N-Hop multi- lateration can be used in ad-hoc sensor networks to address the issue of node location [10]. Results from the techniques mentioned earlier are generated on a single platform, and the best algorithm is then identified by comparison. The main find- ing is that no single algorithm performs more effectively than all others; the conditions (range errors, connectivity, anchor fraction, etc.) dictate which algorithm should be used. [11]. One can perform spatial reasoning by using the values of RSSI from regionally scattered source of data. In a TEU container that is empty, the method is tested. The findings demonstrate how the spatial analysis increases positioning accuracy andis independent of target sensor node's stand position when compared to the current multi-lateration approach. At 18 test positions, The technique succeeds 61.1 percent estimation of position without mistake. 99.4% of tests show positioning errors of up to 1.2 metres. 2.14m is the maximum error [12]. CellSense, an improved RSSI-based fingerprinting algo- rithm, is a probabilistic method that outperforms traditional fingerprinting techniques in terms of accuracy. In urban areas, CellSense has an accuracy of 86.4% [13].

To create a reliable, affordable real-time object localization system, Wi-Fi, Bluetooth, Zigbee, and long-range WAN are the four wireless technologies that are compared. Both localization precision and power consumption are taken into consideration. The process yielded an RSSI value [14], which was then used for trilateration and localization. With an average error of 0.664 metres from the true receiver position, WiFi was found to be the most accurate. WiFi was followed by BLE, which had an error of 0.753 metres. [15]. A hybrid outdoor localization technique using crowd-sourced Data from Wi-Fi signals and sensors incorporated into smartphones to achieve high positioning accuracy while using little power. All local- ization techniques are examined in this study to achieve the crowd-sourced technique. A sensor-assisted matching and a map tile mechanism is used. The hybrid localization technique

performs better than other outdoor localization algorithms, with an average 5% increase in accuracy. [16].

r = Distance between anchor and sensor node

When it comes to resolving the localization issue, Cuckoo

search algorithm outperforms particle Swarm optimisation and bio-geography-based optimisation.The Cuckoo search algo- rithm is founded on the concept of using eggs in a nest as representations of potential solutions, where each egg symbolizes a particular solution. Additionally, the presence of a cuckoo egg signifies the introduction of a new solution into the search process. The increased sensor node range, which boosts localised nodes while lowering localization error, is another factor to take into account. The confidence interval for the Cuckoo search algorithm is on average 97% [17]. The productiveness of WSLA and WSRA in locating a sensor nodehas been demonstrated. Each node in the WSLA obtains the coordinates and distances of its one-hop neighbours during each iteration before using weighted two-dimensional logarithmic search. WSLA has an accuracy of 83.84%, whereas WSRA has an accuracy of 85.92% [18].

While indoor localization has made significant progress, outdoor environments present unique difficulties like LOSobstructions, Multi-Path fading, varying environmental conditions, and interference. One significant research gap in the field of localization is the need for the development of techniques that can accurately estimate the positions of sensor nodes in outdoor environments, particularly when faced with Non- Line-of-Sight (NLOS) conditions. Obstacles such as buildings, trees, or uneven terrain can cause NLOS situations in outdoor settings, resulting in signal reflections and multi-path effects. Traditional localization algorithms, which frequently assume ideal line-of-sight conditions, are challenged by these conditions. This study fulfils a significant gap in existing research by focusing on localization techniques for NLOS scenarios in outdoor environments. The research motivation arises from the need to develop localization techniques capable of accurately

Algorithm 1 Modified 2-Slope 2-Ray Propagation Model

```
Input : $a1, a2, a3, a4, rssi1, rssi2, rssi3, rssi4$
Output : $Coordinates(x, y)$
Calculate Distance ($rssi$)
    $tx\ power = 100dBm$
    $n = 12.912$
    $dist = 10^{((tx\ power - rssi)/(10*n))}$
    return $dist$

$d1 \leftarrow calc\ dist(rssi1)$
$d2 \leftarrow calc\ dist(rssi2)$
$d3 \leftarrow calc\ dist(rssi3)$
$d4 \leftarrow calc\ dist(rssi4)$
$A = np.hstack((-2 * anchor\ nodes, np.ones((4, 1))))$
$b = distances^{(2-np.sum(anchor\ nodes**2, axis=1))}$

$x, y, = np.linalg.lstsq(A, b, rcond = None)[0]$

Print : $(x, y)$
```

1) Path-loss exponent: In the wireless propagation environment, a direct ray and a reflected ray are taken into account by the two-ray, two-slope propagation model. In this model, the near and the far-field regions each assume a different path loss exponent [20].

Near-Field Region: The path loss exponent in the near-field region, which is typically for short distances, is taken to be 2. This represents the spreading loss component and is similar to the FSPM i.e., if ’d’¡100 the following formula is used:

estimating the positions of sensor nodes in NLOS-affected out-door environments. By doing so, the study hopes to improve practical applicability, performance, technology advancement,
and contribute to the existing body of knowledge in the field

where,

$$pl = 20 * (np.\log_{10}(d) + np.\log_{10}(f) + np.\log_{10}(4 * np.pi/c)) \quad (2)$$

of localization.

III. Methodology

A. 2-Slope 2-Ray Propagation Model

In the 2-Slope 2-Ray model [19], the anchor node and sensor node coordinate differences are stacked on next to a column vector ’1’ in a matrix A that is created for the free space propagation model. By comparing the squared distances to the sum of the squared anchor node coordinates, we also create a vector called ”b.” This formula is based on the equation of circle:

pl = Path-loss exponentd = Distance
f = Frequency [2.4 GHz]c = Speed of Light

Far-Field Region: The path loss exponent is considered to be 4 in the far-field region, which typically corresponds to longer distances. The combined effect of the direct and reflected rays yields this exponent, which causes the signal strength to decay with distance more quickly than in the near-field region. In this case, the formula is as follows:

$$pl = 40 * np.\log_{10}(d) + 20 * (np.\log_{10}(f) \quad (3)$$

where,

$$(x-a)^2 + (y-b)^2 = r^2 \quad (1)$$

where,

$$+np.\log_{10}(4 * np.pi/c))$$

x,y = Position of the sensor node (x,y) a,b = Position of the anchor node (x,y)
pl = Path-loss exponentd = Distance
f = Frequency [2.4 GHz]c = Speed of Light

The path loss calculation uses a different path loss exponent (40) compared to the near-field region model.These formulae represent the path loss in decibels (dB) and includes factors such as distance, frequency (2.4 GHz), and c.

In algorithm-1 the position of the four anchor nodes have been initialized to a1,a2,a3 & a4. The corresponding RSSI values for the 4 anchor node have been initialized to rssi1, rssi2,rssi3 & rssi4 respectively. Using the positions of the beacon, path-loss exponent and its respective RSSI value the calculate distance method computes the distance between the target and the beacon. These distances and positions are summed up in a vector and matrix respectively, which are solved using least square method to predict the coordinates of the sensor node.

```
Algorithm 2 Modified Free Space Propagation Model
Input : rssi1, rssi2, rssi3, rssi4 Output : C
1: Calculate Distance (rssi)
2:     tx power = 100dBm
3:     n = 4
4:     $dist = 10^{((tx\ power - rssi)/(10*n))}$
5: return dist
6: di1 ← calc dist(rssi1)
7: di2 ← calc dist(rssi2)
8: di3 ← calc dist(rssi3)
9: di4 ← calc dist(rssi4)
10: a = math.sqrt((an2[0]-an1[0])**2 + (a2[1]-a1[1])**2)
11: b = math.sqrt((an3[0]-an1[0])**2 + (a3[1]-a1[1])**2)
12: x = (di1**2 - di2**2 + a**2) / (2*a)
13: y = (di1**2 - di3**2 + b**2 - 2*a*x) / (2*b)
Print : (x, y)
```

yielding a path loss exponent calculated using equation(2) of2.

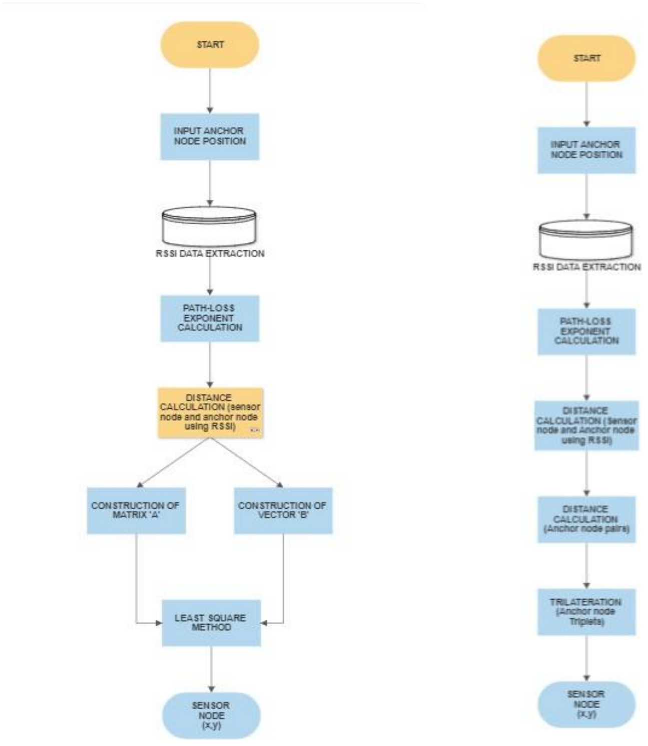

Fig. 1. Workflow of the Models

B. *Free Space Propagation Model*

Euclidean distance is used to calculate the distance between the anchor nodes, and this distance is also used to determine the coordinates of the sensor nodes.

1) *Path-loss Exponent:* In FSPM model, it is typical to assume that the path loss exponent is 2. According to the inverse square law, the power density of a spherical wavefront reduces with double the distance from the origin. [21]. As a result, the received power decreases with distance at 1/d2,

In algorithm-2 the position of the four anchor nodes have been initialized to a1,a2,a3 & a4. The corresponding RSSI values for the 4 anchor node have been initialized to rssi1, rssi2,rssi3 & rssi4 respectively. Using the positions of the beacon, path-loss exponent and its respective RSSI value the calculate distance method computes the distance between the target and the beacon. The distance between all possible unique pairs of the anchors is calculated, all the above values are used to perform trilateration of all possible triplets.

IV. Implementation

a) Dataset Collection: The simulations are carried out in Cooja Network Simulator in order to collect the dataset. With known position of the anchor nodes. The placement of the target nodes is random, and each anchor node's RSSI readings are recorded.

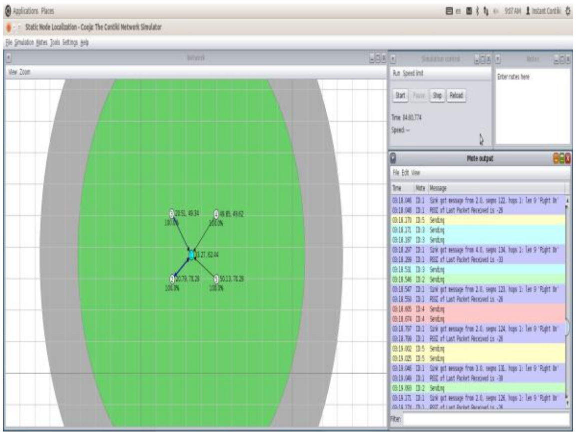

Fig. 2. Positioning of the anchor nodes in the simulation environment

b) Modified 2-Slope 2-Ray Model: When performing trilateration-based localization using the 2-slope 2-ray model, this model displays the estimated positions of a sensor node in comparison to the actual positions. The anchor node coor- dinates are defined as an array, while the estimated sensor node coordinates are initialised in lists. A loop is used to extract the Received Signal Strength values for every anchor node from the rows of the DataFrame. The calculate distance function definition converts the RSSI values into distances by computing the path loss exponent using the appropriate formulae.The anchor nodes' separations are calculated. The trilateration equations are built using a matrix "A" and a vector"b," respectively. By applying the least squares approach to solve the equations, the estimated positions of the sensor nodeare generated.

c) Modified Free Space Propagation Model: The ap- proach trilaterates to predict the coordinates of a target node using the received signal strength indicator (RSSI) data from 4 anchor nodes and their known coordinates. The RSSI data taken from every anchor node were specified, as well as their positions. Using an RSSI value as input, the calculate distance function determines how far the sensor node and its asso- ciated beacon is. The Friis transmissions equation is used to determine the distance,with the exponent of path loss (n) adjusted to 2 and ranging up to 4. The Pythagorean theorem and The distance between two anchor nodes is then calculated using the physical locations of the beacon nodes. We use the trilateration formula to calculate the coordinates of the sensor node based on the spacing between the anchor nodes as well as the distances between the sensor and the anchor nodes.

V. Results

a) Comparison of FSPM & 2S2R Models: The estimated position of the sensor node by the FSPM and 2S2R propaga- tion models is shown in the table below as a summary of the results that were obtained.

Table Icomparison Of The Fspm & 2s2r Propagation Models

Actual Positions		Estimated in 2S2R		Estimated in FSPM	
X	Y	X	Y	X	Y
35.62	59.57	34.50	60.25	33.13	58.83
34.33	58.11	36.79	62.03	35.74	57.18
35.65	61.35	34.77	57.73	36.28	60.76
30.61	59.73	41.63	60.12	34.44	60.17
36.11	58.28	33.98	62.42	35.91	60.06
34.81	59.57	35.78	60.60	33.44	58.74
34.17	58.92	37.04	60.92	39.08	60.28
34.98	57.47	35.50	63.11	37.60	60.67
34.65	58.11	36.01	62.38	33.44	60.36
35.47	61.54	35.28	58.20	35.19	59.99

Figure 3 depicts a scatter plot for FSPM algorithm. The grey dots represent the actual position, while the blue dots represent the predicted position. The graph shows that the prediction accuracy of the FSPM algorithm is lower because the sensor nodes are not widely distributed, mismatching their actual position.

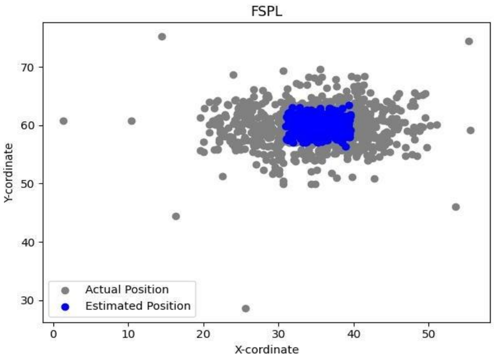

Fig. 3. Predicted positions in FSPM

Figure 4 depicts the scatter plot for 2S2R algorithm. The grey dots represent the actual position, while the blue dots represent the predicted position. The graph shows that the 2S2R algorithm has higher accuracy than the FSPM algorithm in Figure 3 because the sensor nodes are spread out and thus the estimated position coordinates are closer to their actual position.

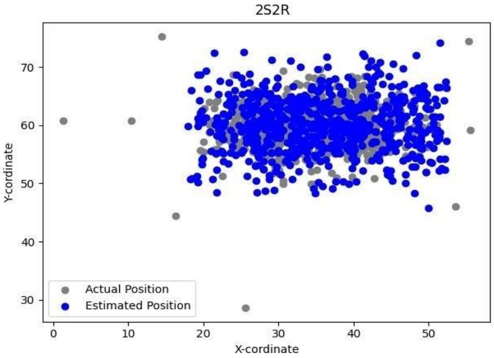

Fig. 4. Predicted positions in 2S2R

Conclusion

To keep an eye on ecological trends and habitat conditions, a WSN is set up in a forested area. Taking into consideration the obstacles and NLOS nature of the environment the 2-Slope 2-Ray and the Free Space Propagation models are modified to localize the sensor node accurately. From the experiments that were carried out the superiority of the 2S2R model over the FSPM highlights the need of taking into account real- world environmental conditions to achieve more precise as well as reliable outdoor localization. Based on our findings, the 2S2R model performs better than the FSPM in determining

he location of the target node, especially when dealing with challenging outdoor settings with obstructions and multi-path fading.

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