Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 44 No. 9
September 2023

Sensor Node Localization Using Machine Learning for Indoor Location Estimation

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Abstract—Localization plays an important role in wireless sensor networks. A system that uses received signal strength indicator (RSSI) measurements, Bluetooth Low Energy (BLE), and RSSI fingerprinting is put forth. The location of sensor node, which is not known, can be found without the assistance of GPS, GPRS, or any satellite service that provides the facility to find the missing object in an indoor environment. BLE beacons are positioned all across the indoor environment to create a network of reference points. These beacons send out signals with distinc- tive identities, which mobile devices can detect and gauge signal strength from. A fingerprinting database is created by gathering RSSI values from various beacons and connecting particular RSSI patterns to well-known places inside the museum. Reducing the number of anchor nodes and improving location accuracy are the key objectives in this situation. Applying the gaussian filter to the algorithm makes sure that all the unwanted signals sent by theanchor nodes will be ignored, only RSSI value will be considered for the process, which will contribute to the increase in accuracy of the end result. When compared to other algorithms, the Cooja simulator evaluation of the algorithm reveals that this approach offers superior precision and accurate positioning.

Keywords—Localization, Bluetooth Low Energy (BLE), RSSI Fingerprinting, Wireless Sensor Network(WSN), K-Nearest Neighbor.

I. Introduction

A WSN is a type of network that consists of a group of spatially distributed autonomous sensors that use wire- less communication to monitor and collect data from the surrounding environment. These sensors are equipped with various types of sensors that allow them to gather data such as temperature, humidity, pressure, and sound. The sensors' data is transmitted wirelessly to a sink, where it is processed and analyzed. The network can be configured in various ways de- pending on the application requirements. For instance, sensors can be arranged in a linear, star, or mesh topology. Wireless sensor networks have many practical applications, including environmental monitoring, industrial process control, home automation, healthcare, and military surveillance. They are often used in situations where it is difficult or impossible to physically access the location being monitored. The process of pinpointing the precise locations of network nodes is known as localization in wireless sensor networks. Range-based and range-free localization strategies are the two main wsn local- ization techniques.Distance or range measurements are used in range-based localization to pinpoint a node's location. This can be done using techniques such as triangulation or trilateration. In triangulation, the location of the target node is predicted by calculating the angle between the target and all the beacon nodes, whereas in trilateration distance is used in-place of angle. [1]. Range-based localization requires nodes to have access to accurate range or distance measurements, which is attained using techniques such as Time-of-Flight, RSS, AOA [2].On the contrary, range-free localization does not require range or distance measurements. Instead, it uses information such as signal strength, connectivity, or hop-count to determine the physical location of a node. Range-free localization algo- rithms typically use techniques such as centroid or DV-hop to estimate node locations. In centroid, the node's location is estimated by computing the centroids of its neighboring nodes. In DV-hop, nodes use the hop-count information in their routing tables to calculate the distance between them and a predetermined collection of anchor nodes. [3]. The choice between range-based and range-free is based on various pa- rameters, which includes accuracy of range measurements, the density of the network, the availability of anchor nodes, and the computational and energy resources of the nodes. Range- based localization typically provides higher accuracy but re- quires more resources, while range-free localization is less accurate but requires fewer resources. Localization has two types: Indoor Localization and Outdoor Localization.Outdoor localization refers to determining the physical location of a device or person outside of a building or other indoor environment. This is often done using GNSS, such as GPS, Galileo, and BeiDou. GNSS systems use satellites to transmit signals to devices on the ground. These signals are then usedto calculate the device's location. The process of locatinga person or device physically inside a building or another indoor environment is known as indoor localization. [4]. When compared to Outdoor environments, Indoor environments have a disadvantage of not being able utilize the support of GPS, GPRS and other available satellite services for the purpose of localization. To keep track of devices that are misplaced in a very crowded area for example a waiting room of a railway station. So, locating each object at frequent intervals becomes necessary in-order to make sure that all required items are in the same position as kept before.

II. Related Work

In order to decrease the impact of shadowing brought on by obstacles that will be dispersed throughout the experiment, this paper presents an RSSI-based localization scheme for WSN. By correcting for distance measurement errors, this algorithm can be used to increase the precision of node localization in obstructed sensor networks. The system will multilaterate a certain number of beacons on each subset to estimate location, and then apply clustering to choose the most likely location that will be consistent with multilateration's number of indi- viduals [5]. The technique outlined is spatial reasoning, which involves examining the correlation between RSSI values from spatially distributed data sources. The method was tested in a vacant shipping container. At 18 test positions, this algorithm has a 61.1 percent accuracy in estimating the position without error, and 99.4 percent of performed iterations reveal posi- tioning errors of up to 1.2 metres. For any position, P13 has a maximum error of 2.14 m. The outcome shows that spatial reasoning obtains more accuracy in position, irrespective of the position of the beacon node when compared with current Multi-lateration approach [6]. The cuckoo search algorithm outperforms particle swarm optimisation and bio geography- based optimisation in this study's analysis of the localization problem. In a 10x10 square area, 200 target and 10 anchor nodes are distributed among the nodes. Additionally, the sensor nodes' transmission range has been set at 2. Additionally taken into account is the sensor nodes' range. More nodes can be localised and the localization error is reduced as the sensor node range increases, the accuracy of cuckoo search is 97 percent [7].The distributed weighted search-based algorithm and it's refinement can be used to determine the location. Each node receives the coordinates and distance details of its 1-hop neighbour during each iteration of the WSLA algorithm. The position is then estimated using a weighted two-dimensional logarithmic search. Using a logarithmic search, the best es- timated position is found, and all nodes then estimate their coordinates and type in accordance with the distribution of the positions that are the most accurate. The research discovered that the suggested approach is more trustworthy than MLE, RSOCP + NCSG, and PSO [8].Creating a reliable, cost- effective real-time system that can localise objects is the main objective. With an eye towards localization accuracy and power utilization, four wireless technologies : Wi-Fi, Bluetooth, Zigbee, and long-range WAN—are contrasted. Tri- lateration was utilised in conjunction with the RSSI value obtained from the process to pinpoint the object's location. Wi-Fi has ultimately been shown to be the most precise technology available with only 0.664m positioning error and was 80 percent accurate in environment with distance of 5m [9]. An improvised RSSI-based algorithm demonstrates that, the proposed algorithm improves localization accuracy and reduces deviation. The experimental outcomes show that the proposed method enhances localization accuracy with-out adding complexity or cost [10]. A unique trilateration

algorithm that uses the RSSI to pinpoint a device in an indoor setting. First, a gaussian filter is used to pre-process the measurement data in order to lessen the impact of the measured noise. Next, localization based on RSSI values is used to estimate transmit power and path loss exponent using novel least-square curve fitting method. The novel trilateration algorithm attains the accuracy of 80% with positioning error of 1.696m [11]. Bluetooth Low Energy (BLE) devices worn by visitors are used to transmit packets that are then received by geo-localized BLE receivers inside the museum, enabling the development of an indoor localization system for precisely tracking people visiting museums or other cultural institutions. A non-linear least squares algorithm combined with a feed- forward neural network process the collected data to produce a position estimate accuracy of less than 1 metre for 90% of cases [12]. To overcome the problem of signal fluctuations affecting the RSSI, several filters and algorithms are usedand to provide an accurate indoor localization solution for medical applications using Bluetooth Low Energy (BLE). The proposed system, which is scalable, economical, and power-efficient, achieves a positioning estimation error below 0.5 m for nearly 95 percent of the readings in Line-of-Sight testing [13]. An enhanced RSSI-based fingerprinting method is put forward for a indoor localization using BLE. By enhancingand classifying data with machine learning algorithms, the technique improves accuracy. Using Random Forest, it over- comes RSSI fluctuations brought on by multipath propagation and other factors, and achieves a high test accuracy of 96%. The suggested remedy is appropriate for IoT and smart city applications [14]. A localization system that works on ZigBee technology is put forth. The collected data was limited asthere was less number of sensor and beacons in the indoor environment,the installation density of the sensor node was set at 0.27 nodes/m square, the estimation error of sensor node position was reduced to 1.5-2m [15]. A CSPR model and fingerprinting, outlier detection, and extended kalman filtering are combined. along with BLE beacons is used to build an application for smartphones that predicts the location. Two approaches were used in the experiment namely: Strategicapproach and aggregate approach.Strategic approach provided better accuracy than aggregate approach. The beacons had better accuracy under the algorithm presented with ¡2.56m at 90 percent when compared to the other approach that was the combination of Propagation Model (PM) + EKF algorithm with ¡3.99 m 15.77% superior to ¡3.04m from the FP + EKF algorithm [16]

III. Methodology

The indoor localization system aims to provide accurate positioning for people visiting museums, cultural institutions, or any indoor environment using BLE technology. The system leverages the ubiquity and low-cost nature of BLE devices, usually found in present-day smartphones or small chip sets, which occasionally transmit packets. To enable accurate local- ization, geo-localised BLE receivers are strategically placed within the museum area to capture the transmitted packets.

These receivers collect the packets and send them to a lo- cator server for further processing. The server employs a feed-forward neural network that has been trained through a measurement campaign in a specific indoor environment. This neural network is essential for accurately estimating the positions of visitors inside an indoor environment. However, the system acknowledges the challenge of signal fluctuations in BLE's received signal strength indicator (RSSI), which can impact localization accuracy. To address this, the system incorporates several techniques. These include examining just one BLE advertising channel, implementing a hard fluctuation elimination filter, and using a weighted Kalman filter to enhance the stability of the RSSI data.

A. RSSI Fingerprinting

RSSI fingerprinting is a technique used in indoor localiza- tion to depict the location of a required node based on RSSI values received from anchor nodes. The working principle of RSSI fingerprinting involves creating a reference database of RSSI fingerprints at known locations within the museum or cultural institution environment. This reference database is generated during a training phase by collecting RSSI measurements from the anchor nodes at different positions. During the localization phase, the target node (sensor node carried by a visitor) receives RSSI values from the surrounding anchor nodes. These RSSI values are then compared with the reference database to find the best match. The system uses algorithms, such as k-nearest neighbors (KNN), to perform the matching process.

The RSSI fingerprints in the reference database are associ- ated with known X and Y co-ordinates of the anchor nodes. By finding the closest match between the measured RSSIvalues and the reference database, this system can predict the accurate position of the device. To enhance the accuracy of fingerprinting, various factors are considered. These include handling RSSI fluctuations caused by multi- path propagation and environmental interference, incorporating advanced filter- ing techniques, and optimizing the database size and density ofreference points. By leveraging RSSI fingerprinting, the pro- posed system can achieve accurate indoor localization without the need for complex infrastructure or extensive calibration efforts.

B. KNN location Detection

The K-Nearest Neighbors (KNN) algorithm is employed in the overall context of the proposed Indoor Localization Systemto detect the location of a target node (sensor node) based on the proximity of neighboring anchor nodes. KNN is a simple yet effective algorithm that leverages the distances between data points to make predictions. In the indoor localization system, the KNN algorithm the adjacent anchor nodes taken into

utilises the known positions (x and y coordinates) of beacons stored in the routing table. When a target node needs to be localised, the algorithm calculates the distance separating the target and the anchor nodes using various methods, such as Euclidean distance. The KNN algorithm then identifies the K nearest beaconsto the target node based on the calculated distance. The value of K, determined beforehand, represents the count of consideration for the

Algorithm 1 RSSI FINGERPRINTING

Input : *a*1*, a*2*, a*3*, a*4*, rssi*1*, rssi*2*, rssi*3*, rssi*4
Output : *Coordinates*(*x, y*)

```
transform (self, rssi)
    tf = []
for observation in rssi do
      tf.append([])
    for beacon in self. beacons do
      if beacon in observation then
    – tf[ 1].append(observation[beacon])
      else
    – tf[ 1].append(self. undetected value)
      end if
    end for
end for
return tf
```

process of localization. Typically, a higher value of K improves accuracy but may increase computational complexity. Once the K nearest anchor nodes are identified, the algorithm assigns a weight or importance to each anchor node based on its proximity to the target node. This weighting can be linear or based on distance decay models.

Algorithm 2 K-Nearest Neighbour

Input : *Datasetcontainingfingerprints*
Output : *Coordinates*(*x, y*)
1: *x_train, x_test, Y_train, Y_test* = *train_test_split*(*X, y, test_size* =0.2*, random_state* = 4)
2: knn = KNeighborsClassifier(*n_neighbors* = 7)
3: knn.fit(*X_train, y_train*)
Print : *knn.predict*(*x_test*)

In algorithm 1 a1, a2, a3 and a4 are the co-ordinates of the anchor node , rssi1, rssi2, rssi3 and rssi4 are the received signal strength values of a1, a2, a3 and a4 respectively. These values are then fingerprinted using the transform function which checks for signals from sensor nodes that already exist in the observation table and appends it to the corresponding row, if not it adds a new row and appends the values to the corresponding row.

The dataset, which consists of fingerprints and the labels that go with them, is split into two sets: an X train set and a y train set for training, and an X test set and y test set for testing. The train test split function from the Scikit-Learn library is used to split the data with a test size of 0.2 (20% of the data) and a random state of 4. The split's repeatability is ensured by the random state. The parameter n neighbors is set to 7 when creating an instance of the KNeighborsClassifier class. A data point's class label is determined using the KNN algorithm based on the majority class of its k nearest neighbours.

The weights are used to influence the final position estima- tion. Finally, the algorithm combines the weighted beacons positions to find the location of the device. This can be achieved through different methods, such as centroid calcu- lation, weighted averaging. By employing the KNN algorithm for location detection, the indoor localization system benefits from its simplicity and flexibility. The algorithm can handle non-linear relationships between anchor nodes and the target node's location, making it suitable for complex indoor en- vironments. However, it is important to carefully determine the value of K and consider the potential trade- off between accuracy and computational overhead.

IV. Implementation

Fig. 1. Node deployment

A. Node Creation

Node creation refers to the process of establishing and configuring the various components involved in the system, including the geo-localized Bluetooth Low Energy (BLE) receivers, anchor nodes and sensor nodes. Node creation for these receivers involves the physical installation and placement of the receivers throughout the museum or cultural institution area. Anchor nodes are stationary reference points within the museum environment with known x and y coordinates. Sensor nodes, on the other hand, are the BLE devices carried by the visitors. Node creation for these sensor nodes involves configuring the BLE devices to operate in the appropriate mode for localization. This may involve setting up BLE advertising and packet transmission parameters, as well as ensuring the devices are properly powered andequipped with the necessary software or firmware. Once the geo-localized BLE receivers, anchor nodes, sensor nodes are created and configured, the system is ready for data collection and subsequent localization.

B. Node Deployment

The approach uses Bluetooth beacons placed inside an indoor environment which send out the RSSI values for the sensor nodes within the range, then the RSSI values are compiled into an excel sheet which is used for the process of RSSI fingerprinting.Multiple signals are sent out from the sensor nodes but only the RSSI values are considered and then the fingerprinted values are used in K-Nearest Neighbouralgorithm to depict the location of the required device by con- sidering the K-Nearest positions using RSSI values. Gaussian filter is applied to the above-mentioned values in order to remove any unwanted signals sent by the sensor node that may interfere with accurately predicting the device's position. In the image, there is a depiction of an anchor node passing RSSI values to a sensor node in the context of an indoor localization system. The image illustrates the communication and data exchange between these two components. The anchor node is represented as a stationary device positioned at a specific location within the indoor environment. It is depicted as a

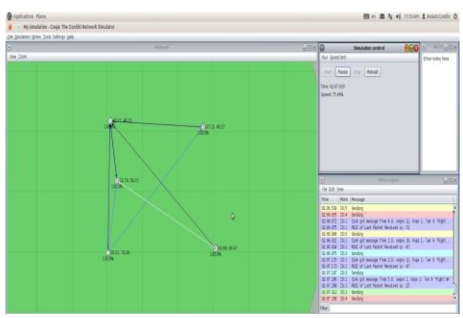

Fig. 2. Dataset Collection

small icon or symbol, typically denoted by a distinct shapeor color. The anchor node is equipped with a transmitter and receiver to facilitate wireless communication. The sensor node, is a mobile device carried by a visitor or user within the indoorspace. It is shown as another symbol, possibly resembling a smartphone or wearable device. The sensor node is designedto receive signals from the anchor node and collect relevant data for localization purposes. The scalability and optimization of the system have also been assessed.

C. Dataset Collection

In the indoor localization system using Bluetooth Low En- ergy (BLE), data collection involves capturing packets trans- mitted by visitors' BLE devices and obtaining the necessary coordinates of anchor nodes and sensor nodes within the museum or cultural institution. To begin the data collection process, geo-localized BLE receivers are strategically placed throughout the museum area. These receivers continuouslyscan for BLE signals emitted by visitors' devices. The signals contain packets that carry information such as the unique device identifier, timestamp, and RSSI. In addition to BLE receivers, the co-ordinates of the anchor and the sensor nodes are also required for the system to properly estimate the location. The anchor nodes are stationary reference points within the museum with known x and y coordinates. These coordinates serve as a basis for the location calculations.The BLE devices carried by the visitors act as targets, and their x and y coordinates are the positions to be estimated. Tocollect the necessary coordinates, a prior setup is required. The position of the beacons are determined and recorded during system deployment phase. These coordinates represent fixed locations within the museum environment. For the sen- sor nodes, which are carried by the visitors, their x and y coordinates are obtained through various methods. This can include manual input by the visitors during registration or datacollection, or it can be acquired through additional sensors or technologies integrated into the BLE devices. By collectingthe packets transmitted by the BLE devices and having the co-ordinates of the anchor and sensor nodes, the system has the essential data to proceed with the subsequent steps of processing, localization, and position estimation.

V. Results

The results obtained clearly showcase the effectiveness and accuracy of the localization approach. The system has achieved remarkable outcomes through rigorous testing and measure- ments. The results reveal that the position estimate accuracy achieved is below 1 meter, indicating precise localization capabilities within the museum or cultural institution. This level of accuracy is crucial for providing accurate visitor track- ing and positioning information. Furthermore, the system's performance has been evaluated using various metrics, such as error analysis and statistical measurements. These evaluations confirm the system's ability to consistently provide reliable position estimates for visitors in line-of-sight testing scenarios.

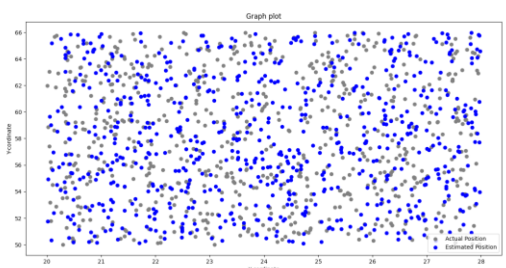

Fig. 3. Comparison of Estimated Position & Actual Position

Figure 3 shows the scatter plot where the actual and predicted positions are considered for x and y axis of the plotting graph. The grey colored dots depict actual position and the blue colored dots depict the predicted position.

The results indicate that the system can handle large number of visitors while maintaining low power consumption and cost- efficiency. This scalability is vital for accommodating varying visitor densities in busy museum environments. Overall, the obtained results validate the system's capability to accurately localize individuals within the indoor space, facilitating en- hanced visitor management, logistics, and location-based ser- vices. The achieved position estimate accuracy, combined with scalability and optimization, highlights the system's potential to improve operational efficiency and provide valuable insightsin museum and cultural institution settings.

VI. Conclusion

The Indoor Localization System using BLE technology has shown promising results and significant potential for enhancing visitor experiences and operational efficiency within museum and cultural institution environments. By leveraging the capabilities of BLE devices and geo-localized BLE re- ceivers, the system achieves accurate position estimation of visitors. Through the utilization of techniques such as RSSI fingerprinting, KNN algorithm, and data augmentation, the system overcomes challenges related to signal fluctuations and environmental factors, ensuring reliable and precise localiza- tion. The created routing table serves as a valuable reference for positioning calculations. The system's performance, as demonstrated by the achieved position estimate accuracy be- low 1 meter, showcases its effectiveness in providing accurate location information for visitors. The scalability and optimiza-tion aspects of the system contribute to its suitability for handling large visitor densities while maintaining low power consumption and cost-efficiency.

The findings obtained from this experiment indicate that the proposed system has the capability to transform visitor man- agement, internal logistics, and location-based services within museums and cultural institutions. The accurate localization capabilities offer opportunities for personalized experiences, crowd monitoring, and efficient resource allocation. In future, researches and developments in this area can lead to more ad-vanced and robust indoor localization solutions, contributing to the evolution of smart and interactive museum environments.

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