Machine Learning Based Mobile Robot Localization in Indoor Environments

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Abstract*: The mobile robot Indoor Positioning Systems (IPS) are widely used in the automation industry to find the location of moving robots in indoor environments. Existing IPS are expensive, and designs are complex. Moreover, the requirement for further installation work seems to be a common problem in these applications. This paper proposes a simplified localization technique based on the Received Signal Strength (RSS) by employing Machine Learning (ML) algorithms. The collected Received Signal Strength Indicator (RSSI) data from three different anchor nodes in the testbed has been trained using supervised learning algorithms to estimate the mobile robot's geographical location. During the experiment, several algorithms were investigated and Decision Tree Regression (DTR) algorithm outperformed with 28.84 RMSE and 0.9 R^2*

Keywords: *Indoor Positioning Systems (IPS), Machine Learning, IoT, RSSI, Mobile Robots*

1. Introduction

The Internet of Things (IoT) can be identified as the extension of internet-connected devices such as sensors and actuators for a specific purpose. In modern transportation, medicine, elderly care, agriculture, smart building, smart cities, energy management, and other systems, the deployment of IoT devices and their applications are significant. Many mobile robot applications require localization (Moreno, 2002). Some examples are humanoid robots, unmanned rovers, entertainment robots, elderly assisted robots, pick-and-place robots, and Automated Guided Vehicles (AGVs). Some of these applications require very precise localization techniques which require sophisticated navigation or localization techniques such as vision cameras, magnet stripes, or laser sensors (Jiménez, 2019). These high-precision localization techniques are expensive and challenging to implement during the operation unless implemented during the initial stages. However, some applications require more minor precision localization requirements for mobile robots. For those applications, it is essential to implement a technique to quickly set up with less hardware where IoT can dominate. Much research works on emerging applications has been conducted in the field of IoT and, indoor localization falls under the Location-Based-Services (LBS) IoT applications. This (Indoor Positioning System) IPS, a set of wireless sensors, are strategically installed in the indoor environment and these nodes communicate with the mobile sensor node (mobile robot). Depending on the application scenario, the data transmission can be done as a Local Area Network (LAN) or an IoT-based cloud architecture (Hasan, 2015).

Furthermore, location-based IoT applications are widely used in industrial and commercial applications due to their low cost and small size (Maduranga, 2021). In this acquisition Wireless Sensor Network (WSN) associated with IoT, used for storing, monitoring, and processing data on a remote storage server. WSN-based indoor localization can utilize a variety of measurement methodologies, including time-based, angle-based, and RSS-based observations. In a WSN, the RSS represents the energy level of the received signal from the deployed sensor nodes. The RSS signal energy was quantized to generate the RSSI, which was then processed for indoor position estimation. RSS-based localization estimates the position of an object or a person in an indoor setting. Several algorithms are being developed to estimate position, such as deterministic, probabilistic, and machine learning. With a deterministic method, triangulation and trilateration techniques are commonly used. With fingerprinting techniques for diverse environments, machine learning-based supervised learning, and probabilistic approaches are applied. The RSSI measurement data are used in the presented research for position estimation using deterministic and machine learning techniques. The RSSI data for the study was collected from the dataset presented (Weerasinghe, 2019). The obtained data was then run through a localization algorithm, and the RSSI-based position estimate algorithms were compared.

The rest of the paper has organized as follows. Section II presents the recent works on ML-based localization.

Section II explains the ML model developments and implementation. The section IV shows the comparative performance analysis of each algorithm, while section V concludes the findings.

2. Related Work

According to the literature, time-based, angle-based, RSS-based, or a combination of these three techniques are commonly used for signal gathering in indoor localization (Zhang, 2010). The time of arrival (TOA) [8] and the time difference of arrival (TDOA) (Maduranga, 2014) are time-based measures related to transmission time that can be used for position estimation. The angle of arrival (AOA) (Farid, 2013) is used as an angle-based position estimation that requires a highly advanced directional antenna as the beacon node for angle measurements. Additionally, indoor localization can be accomplished via triangulation and trilateration (Zhu, 2013) techniques. According to the literature, the RSS-based trilateration localization approach is the most often used algorithm due to its ease of use and broad applicability range. Furthermore, researchers used neural network strategies for WSN localization at the dawn of machine learning (Alsheikh, 2014), (Di, 2007) because they are well suited for prediction from sample data to a specified output.

Any wireless-based range and positioning system where the distance is estimated based on the strength of the received signal from the sending node relies on the correlation between the RSSI and the distance (Zhang, 2010), (Ahn, 2010). (Payal, 2014) A cost-effective localization framework proposes a WSN-based localization approach based on a Feed-Forward Neural Network (FFNN). (Sugano, 2006) employed ZigBee-enabled transceivers, as well as embedded microcontrollers and microprocessors, in their RSSI-based localization tests. Rajeev Piyareet et al.'s work on a WSN-based data acquisition system using a ZigBee device requires a separate microcontroller unit to gather data (Piyare, 2013).

The two approaches of location estimation, trilateration and Machine Learning (ML), are compared in terms of performance. Based on the findings, we chose the most appropriate position estimation technique for the models from the abovementioned options. It should be emphasized that because RSSI readings are relatively unstable in terms of time and position, proposing a highly stable and accurate localization technique is challenge. Therefore, the RSSI technique does not give realistic values by using deterministic models, like time, angle, or geometry-based techniques. The paper addresses the issue of giving a validated solution for highly approximated localization using ML for RSSI.

Model Development And Training

For the implementation of study, a dataset introduced by (Weerasinghe, 2019) was utilized after filtering the outliers from the original dataset following the method given in the same study. Then the traditional trilateration technique was implemented using the given dataset. Finally, machine learning models also were trained and tested using the same dataset.

A. Dataset

WSN area is a 293.8 cm x 274.6 cm obstacle-free indoor space surrounded by walls. The hardware setup of the WSN used for collecting data (Weerasinghe, 2019) consists of three fixed beacon nodes and one mobile node. All beacon nodes and the mobile node in this WSN were Wi-Fi sensors that were based on IEEE 802.11 standard. The mobile node scans and records the Received Signal Strength as RSSI of three beacon nodes. The beacon nodes are fixed in known arbitrary corners.

In contrast, the mobile node has moved in x and y directions without changing the z directions displacement to limit the study to a 2D localization problem. This summarizes that the input data used for the developed models in this study are RSSI readings of three beacon nodes. The RSSI data were collected from 34 known sample positions concerning three beacon nodes. The output data are the mobile node's corresponding x and y coordinates (robot). The dataset was composed of 1200 data points and 70% of the dataset was used for training and the rest was used for testing.

B. Prediction Models Development

This study compares different machine learning models that can be used for 2D localization. We have accommodated the trilateration proposed in (Weerasinghe 2019) to present a complete study to compare with developed machine learning models. The models used in this study are as follows.

1) *Trilateration*: The linear relationship between the RSSI vs. distance (between a beacon node and the mobile node) on the log scale can be represented by,

$$\mathrm{RSSI} = -(10 n \log_{10} d + A) \tag{1}$$

where ;
d - distance from the blind node to the reference node
n - Signal propagation constant

A - Received Signal strength at a 1m distance

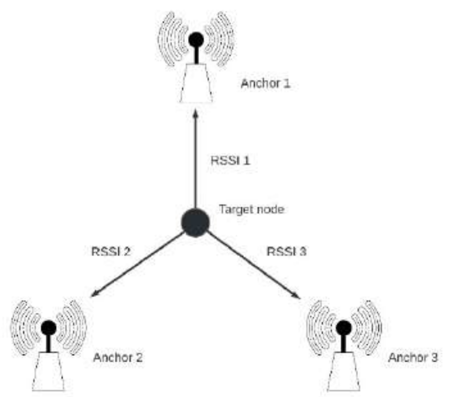

Fig.1: RSSI-based localization

The study (Weerasinghe, 2019) has calculated and presented the propagation constant $(1/10n)$ and the constant A for the dataset used in this study. Using these constants, we were able to calculate the distance from each beacon node to the mobile node and after the position of the mobile node (i.e., x,y coordinates of the mobile node) was estimated using the Euclidian distance approach as presented in (Weerasinghe, 2019).

2) Linear Regression: When it comes to machine learning, it is always advisable to test the data fitting with a fundamental technique like Linear Regression (LR). Where x is the independent variable and y is the dependent variable as expressed in Eq.2.

$$y = \theta_0 + \theta_1 x + \varepsilon \quad (2)$$

3) Polynomial Regression: As the second step, we have developed a 4th order Polynomial Regression (PR) model. The 4th order polynomial model in one variable is given by Eq.3.

$$y = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \varepsilon \quad (3)$$

4) Lasso Regression: This is a modification of linear regression, where the model is penalized for the sum of absolute values of the weights as indicated in the objective function, Eq.4. The degree of shrinkage is controlled by $\boldsymbol{\lambda}$. The predictive model is constructed using simply the residual sum of squares, which denotes that all features are taken into account. As the residual sum of squares gets closer to infinity, it eliminates more and more features.

$$L = \sum_{i=1}^{n} \left(y_i - \sum_j x_{ij}\beta_j\right) + \boldsymbol{\lambda}\sum_{\boldsymbol{i=1}}^{\boldsymbol{p}} |\beta_j| \quad (4)$$

5) Random Forest Regression: Related works shows the potential of using RFR in localization problem. A supervised learning technique called Random Forest Regression leverages the ensemble learning approach for regression. The ensemble learning method combines predictions from various machine learning algorithms to provide more accurate predictions than those from a single model.

6) Decision Tree Regression (DTR): A decision tree creates tree-like models for classification or regression. It incrementally develops an associated decision tree while segmenting a dataset into smaller and smaller sections. The outcome is a tree containing leaf nodes and decision nodes.

7) Support Vector Regression (SVR): The Support Vector Regression (SVR) is heavily used in localization works (Jondhale, 2022). An approach for supervised learning called support vector regression is used to forecast discrete values. The SVMs and Support Vector Regression both operate on the same theory. Finding the optimum fit line is the fundamental tenet of SVR. The hyperplane with the most points is the best-fitting line in SVR.

8) Feed Forward Neural Network (FFNN): To provide a complete study, it was decided to try a Feed-Forward Neural Network (FFNN) as well. The neural network used in this study consisted of one hidden layer with ten neurons. The model was implemented and trained using the MATLAB R2020a (MathWorks, 2022) neural network toolbox. The model was trained up to 35 epochs using the Levenberg-Marquardt training algorithm (Yu, 2018).

The above-mentioned algorithms were trained using Python with the aid of ML libraries Scikit-Learn (Kramer, 2016). During the training the data set split into 30% for testing and 70% for training. Hyperparameters of algorithms were tuned to obtained more accurate results. Where, Maximum depth of the DTR model was set to 25.

3. Results and Discusison

Considering all 8 methods, we have compared the performance of all the models in terms of the Root Mean Square Error (RMSE), Pearson correlation coefficient (R) and training time. The comparison of the results is given in the Table 1. Since the trilateration approach is a mathematical approach rather than a machine learning training method it was excluded from the training time comparison. A few samples estimated form DTR algorithms are shown in the Fig.2. Finally, the average error made by each algorithm are shown in the Fig.3.

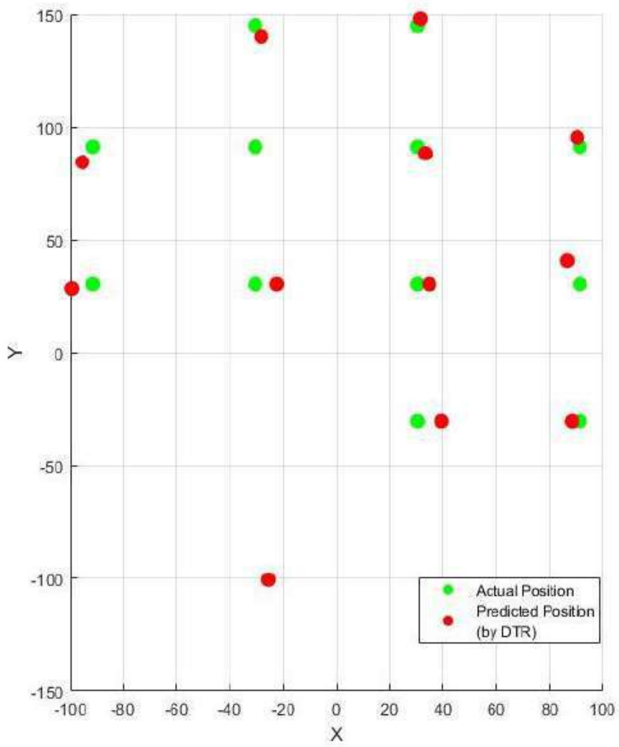

Fig.2: Actual positions and estimated positions using DTR

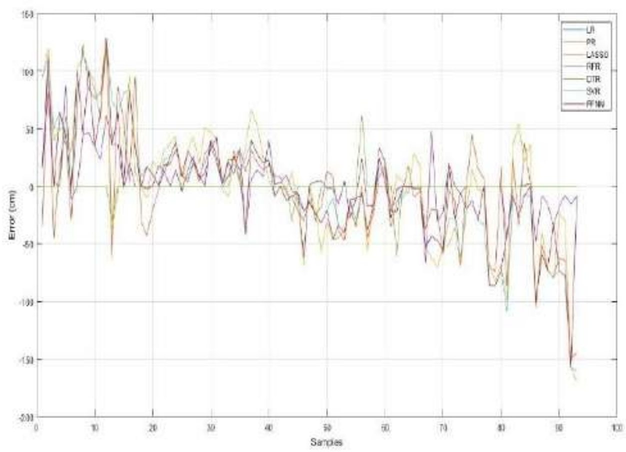

Fig.3: Estimation error in each algorithm

The RMSE given in the following equation is a well-used indicator to identify the accuracy of a model. This denotes the accuracy of the predictions given by the model.

$$RMSE = \sqrt{\frac{\sum(predicted - actual)^2}{number\ of\ samples}} \quad (5)$$

The Pearson correlation coefficient (R) given in the following equation expresses the correlation between predictions and the actual coordinates as per Eq.5.

$$R = \frac{\sum(x_i - \bar{x})(a_i - \bar{a})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(a_i - \bar{a})^2}} \quad (6)$$

where x_i – predictions, $\bar{x}$ – mean of the predictions, a_i – actual data, and $\bar{a}$ – mean of the actual data

Then the training time is an important indicator that identifies how fast a model can be trained and built.

We have developed independent models to predict both x coordinate and y coordinate of the mobile node using RSSI of beacon nodes and evaluate the developed models using RMSE, Pearson correlation coefficient, and training time. The RMSE, Pearson correlation coefficient and training time for the training dataset is given in Table 1.

Observing the results, it is clear that trilateration gives the least accuracy, which justifies the importance of looking at other indoor localization methods for higher accuracy. The DTR has outperformed all other models by giving the least RMSE and highest R. However, the RFR also has produced results closer to the DTR model. It is also interesting to note that both RFR and DTR models have taken the same training time. When considering the training time, the LASSO has been trained within 20 seconds which is the shortest training time.

4. Conclusion

Table 1. Performance Comparison of localization models

Model		**Performance Indicators**		
		RMSE	**R**	**Training Time (s)**
Trilateration	x	131.63	0.101	N/A
	y	110.44	0.139	N/A
LR	x	77.54	0.270	30.0
	y	71.75	0.419	30.0
PR	x	68.14	0.436	430.2
	y	57.21	0.631	430.2
LASSO	x	77.54	0.270	20.4
	y	71.75	0.419	20.4
RFR	x	34.65	0.854	30.4
	y	32.79	0.879	30.4
DTR	x	28.34	0.903	30.4
	y	28.84	0.906	30.4
SVR	x	73.43	0.345	40.4
	y	67.56	0.486	40.4
FFNN	x	55.08	0.803	100.3
	y	51.08	0.801	100.3

In this work, we have done a comparative study on using the supervised algorithms for mobile robot localization. The supervised learning algorithms consistently outperformed classical algorithms such as trilateration. Statistical analysis shows that machine learning approaches have significantly less estimation error, and the DTR has given the best accuracy with adequate training time. The DTR models give the best accuracy out of the other machine learning models trained. This concludes that it is could be important to test machine learning approaches before going for the trilateration approach in indoor localization problems.

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