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Research Article

Indoor Positioning Algorithms-A comparative Study

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Abstract

An indoor positioning system (IPS) is used to locate objects or people inside a building using radio waves, magnetic fields, acoustic signals, or other sensory information collected by mobile devices. Positioning systems have played a major role in people's lives since the GPS satellite technology became publicly available in the late 90's. Today almost everyone has a device with positioning capabilities like a smartphone, tablet, GPS tracking device or a watch with built-in GPS. An IPS system using recently introduced iBeacon technology which utilizes Bluetooth Low Energy (BLE) is proposed. Three different classification algorithms:- K Nearest Neighbor, Naive Bayes, Support Vector Machine are implemented and their performances are analyzed

Keywords: *Received Signal Strength Indicator, Universally Unique Identifier, K Nearest Neighbor, Support Vector machine, Bluetooth Low Energy,*

1. Introduction

Satellite-based positioning doesn't work indoor, but other technological standards have emerged that make indoor positioning possible. Positioning indoor is more complicated than outdoor positioning using GPS because a certain infrastructure needs to be in place indoor. Shopping centres, airports and museums are just some organizations where indoor positioning would bring great benefit to people. With indoor positioning systems, organizations can deliver location-triggered content, location-based advertising and much more. The indoor positioning market is estimated to grow to $4.4 billion by 2019 with strong demand in healthcare, retail, hospitality, travel and other sectors. IPS provides an opportunity for organizations to engage customers inside large indoor spaces with their brands, their products, their partners or anything that helps them to further increase customer relationships and sales.

The Bluetooth has been used for indoor localization since it is a cost effective and easy-to-deploy solution. iBeacon is a small device which transmits particular information in a defined radius and in regular intervals. As soon as a mobile device (a smartphone) gets within this radius, it can receive such information and based on this, it can perform an action. Considering low consumption of BLE, such a device can be powered by a coin battery for up to two years. The iBeacon is the Apple's implementation of BLE wireless technology to create a different way of providing location-based information services to mobile devices. It acts as an emitter continuously broadcasting Bluetooth signals, each signal contains a Universally Unique Identifier (UUID) and a Received Signal Strength Indicator (RSSI).

In this system, we used an RSS-based algorithm as our major location-estimation method because it is simple to obtain the RSSI data from iBeacon without requiring any specialized hardware, compared to other localization methods such as time of Arrival (TOA), Angle of Arrival (AOA), and Time Difference of Arrival (TDOA).We also carried out a comparative study of three classification algorithms –KNN, Naive Bayes and Support vector Machine. The improvement of public Wi-Fi networks and beacon technology, in combination with more advanced smartphones that can handle Location based services and contribute to a growing interest in IPS. The deployment of the infrastructure is becoming more pervasive and more cost-effective, while devices are becoming more sophisticated, applications more contextual and relevant, and more users are always online.

The rest of the paper is organised as follows: section two deals with the literature survey, section three describes the architecture of the system, hardware and software requirements, section four explains the implementation, section five gives performance analysis of various schemes, finally section six is the conclusion and future work.

2. Literature Survey

A mobile-based indoor positioning system using mobile applications (APP) with the iBeacon solution based on the Bluetooth Low Energy (BLE) technology is proposed by Cheng-Chung Fang,(*IEEE,2015*), to increase the efficiency in the emergency room, Implemented the Received Signal Strength (RSS) based localization method to estimate the patients' locations.

Nhan Vo Than Ngo suggested A two-step procedure (IJECE,2016)in which severe variation in the received signal strength is minimized during the first step via convex optimization, and distance metric learning is then used to estimate a more accurate location. : This method make use of localization algorithm aims to reduce the variance of RSS fluctuation and maximum distinguishable among groups of samples belonging to different RPs, thus facilitating a more accurate estimation of location.

Pavel Kriz, FilipMaly, and Tomas Kozel, (Hindawi 2016) in their paper, "Improving Indoor Localization Using Bluetooth Low Energy Beacons", to compare the measured fingerprint with the database, the *k*-Nearest Neighbors (*k*-NN) in Signal Space method was used. This method tries to find *k*of the nearest fingerprints from the database by means of, for example, Euclidean distance. In this way we get *k* locations and by their combinations we estimate the position of the device to be localized. The localization of stationary objects based on WiFi, Bluetooth Low Energy, and their combination has been evaluated using the data measured during the experiment in the building. Several configurations of the transmitters' arrangement, several ways of combination of the data from both technologies, and other parameters influencing the accuracy of the stationary localization have been tested.

Wenzhe Zhang, Lei Wang, Zhenquan Qin, Xueshu Zheng, Liang Sun, Lei Shu Guangdong (IEEE,2014) In their paper, An Improved Naive Bayes Simple Learning Approach for Accurate Indoor Localization explains an improved Naïve Bayes Algorithm taking into account zero conditional probability is implemented, INBS outperforms traditional Naive Bayes and *k*-NN algorithms

2.1 Indoor Position Technologies

A comparison of different indoor position technologies in terms of various parameters is given in Table [1].

Table 1

	WI FI	Bluetooth	UWB
Ranging Technology	RSSI Fingerprinting	Proximity, Short Range RSSI	Multilateration
Measurement Error	3-15m	2-3m	0.1-0.3m
Position Update Rate	1Hz	1 Hz	4-10 Hz
Operating Range	50m	>10m	40m
Frequency Band	2.4 GHz ISM	2.4 GHz ISM	3.1-10 GHz UWB ISM
Power Consumption	High	Low	Medium-Low

3.Proposed System

3.1 System architecture

In the proposed system, Bluetooth is preferred rather than wifi because of the low power requirement. The mobile APP scans Bluetooth signals in every 5 seconds from the iBeacon in the background and uploads the beacon information to the system server. All the data are transmitted through GPRS.

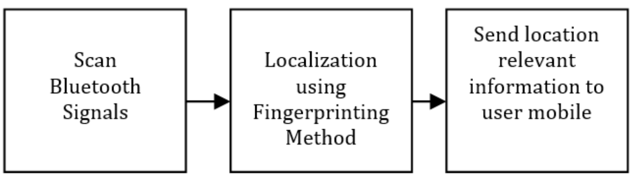

Figure 1

The server side application deals with data saving, reading and mapping. It maps the measured RSSI values sent from users mobile with values already saved in the database. Location identification phase is performed on the server side. The last component is the monitoring side, in which authorized staff can access the location information of users through a web browser or mobile device. The monitoring side is designed as a mobile app, which also has features to send to users mobile location relevant information.

3.2 System Requirements

A BLE iBeacon, computer with processor i3 or above, android device with ARMV7 processor. Windows-10, Java, XML, PHP5, MySql, Apache, Android Studio 1.5.1, Android SDK-API 17 or Higher, Python-scikit-learn, numpy package etc

4. Implementation

In this work besides KNN algorithm, used two other classification algorithms , Naive Bayes and SVM for localization.

4.1 Data Acquisition

The mobile APP scans Bluetooth signals every 5 seconds from the iBeacon in the background and uploads the beacon information to the system server. All the data are transmitted through GPRS.

4.2 Fingerprint Construction

In offline mode, a fingerprint database (also called radio map) is constructed by measuring sufficient number of RSS samples at Receiving Points of interest around the target site and storing this information in the database. The database is updated when a significant change is anticipated in a radio environment, e.g., deploying new access points.

4.3 Location Determination

In online mode a current location is estimated by measuring RSS samples online and matching those against the RSS samples in the radio map that are associated with each RP using any localization algorithm in the server and send position relevant information to the users mobile.

4.3.1 KNN Algorithm

It is a nonparametric supervised learning algorithm where new objects are classified based on a similarity measure. The main idea of the KNN technique, (Hindawi 2016) is based on the calculation of the distance between the measured RSS value obtained in the online phase and the location information of the RSSI database – Fingerprinting. Then the similarity between data and training set is calculated using Euclidean distance

4.3.2 Naive Bayes

Naive Bayes algorithm (IEEE,2014) is the algorithm that learns the probability of an object with certain features belonging to a particular group/class. In short, it is a probabilistic classifier. The Naive Bayes algorithm is called "naive" because it makes the assumption that the occurrence of a certain feature is independent of the occurrence of other features. Bayes theorem provides a way of calculating posterior probability P(c/x) from P(c), P(x) and P(x/c).

Bayes' Theorem for Naive Bayes Algorithm

In a machine learning classification problem, there are multiple features and classes, say, $C_1, C_2, \ldots, C_k$.

The main aim in the Naive Bayes algorithm is to calculate the conditional probability of an object with a feature vector $x_1, x_2, \ldots, x_n$ belongs to a particular class C_i,

4.3.3 Support Vector Machine

A Support Vector Machine (IEEE,2011) is a supervised machine learning algorithm which can be used for both classification and regression problems. The main idea is to identify the optimal separating hyper plane which maximizes the margin of the training data. It not only classifies the existing dataset but also helps to predict the class of the unseen data.

5. Performance analysis.

The performance evaluation of various classification algorithms and their comparison is carried out.

5.1 Dataset

The training data set contain the information for localization. It includes intensity values from 520 different beacons installed in 4 floors of 3 buildings, along with latitude, longitude, floor id and building id. A training data set is prepared to train the model. When testing data is given, unknown class (building id) is calculated using the trained model. Table 2.

Table 2 sample data set

WAP1	WAP2	WAP3	WAP P520	Latitude	Longitude	Floor id	Building Id
100	100	-83	100	-7515.91679	4864889.66291668	1	0
-71	-73	100	100	-7674.78528	4864934.1760907	2	1
100	100	100	100	-7366.08527	4864976.10424104	0	2

The intensity values are represented as negative integer values ranging -104dBm (extremely poor signal) to 0dbM. The positive value 100 is used to denote when an access point was not detected

5.2 K Nearest Neighbor Algorithm

The kNN algorithm is implemented with different values of "k". The summary of evaluation is in table 3.

Table 3. Summary of evaluation of kNN

	Precision	Recall	F1 Score
K = 5	0.95	0.94	0.94
K = 10	0.95	0.93	0.93
K = 15	0.93	0.91	0.91
K = 20	0.92	0.9	0.9

kNN algorithm with different values of k such as 5,10,15 and 20is applied in the data set. It is observed that the precision and recall increases with lower value of k.

The classification report and confusion matrix of kNN is given below:

```
**********************************************************************
KNN Algorithm

**********************************************************************
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
          metric_params=None, n_jobs=1, n_neighbors=5, p=2,
          weights='uniform')
Classification Report KNN
             precision    recall  f1-score   support

          0       1.00      0.90      0.95       536
          1       0.83      0.99      0.91       307
          2       1.00      0.96      0.98       268

avg / total       0.95      0.94      0.94      1111

Confussion Matrix-KNN
[[485  51   0]
 [  2 305   0]
 [  0  10 258]]
**********************************************************************
```

Figure 2. Classification Report and Confusion Matrix of kNN

5.3 Naïve bayes

The summary of evaluation using Naive bayes in positioning is given in table 4

Table 4 Summary of Evaluation Naïve bayes

Precision	0.92
Recall	0.90
F1 Score	0.90

The classification report and confusion matrix of Naïve Bayes is given below

```
**********************************************************************
NaiveBayes Algorithm

**********************************************************************
GaussianNB(priors=None)
Classification Report-Naive Bayes
             precision    recall  f1-score   support

          0       0.99      0.85      0.92       536
          1       0.78      0.98      0.87       307
          2       0.92      0.92      0.92       268

avg / total       0.92      0.90      0.90      1111

Confussion Matrix-Naive Bayes
[[457  64  15]
 [  2 300   5]
 [  1  21 246]]
**********************************************************************
```

Figure 3. Classification Report and Confusion Matrix of Naïve Bayes

5.4 Support Vector Machines

The summary of evaluation of SVM algorithm in positioning is given in the table 5

Table 5 Summary of Evaluation of SVM

Precision	0.82
Recall	0.25
F1 Score	0.10

The classification report and confusion matrix of SVM is given below:

```
*********************************************

Classification Report-SVM

             precision    recall  f1-score   support

          0       1.00      0.01      0.01       536
          1       1.00      0.01      0.01       307
          2       0.24      1.00      0.39       268

avg / total       0.82      0.25      0.10      1111

Confussion Matrix-SVM

[[  3   0 533]
 [  0   2 305]
 [  0   0 268]]
**********************************************************************
```

Figure 4. Classification Report and Confusion Matrix of SVM

6.1 Comparison of Performance of Algorithms

Three classification algorithms namely kNN, Naïve Bayes and Support Vector Machines are implemented. Summary of evaluation is given in Table 6

Table 6 Comparison of Accuracy

	Class A	Class B	Class C
SVM	0.00559701	0.006515	1
Naïve Bayes	0.85261194	0.977199	0.917910448
KNN	0.90485075	0.993485	0.962686567

The Figure 5. shows the chart of the accuracy of kNN, Naive Bayes and SVM

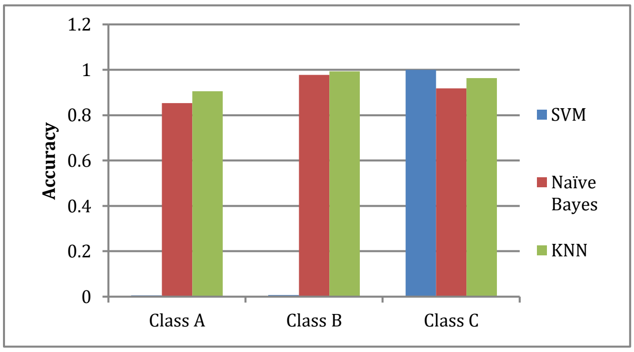

Figure 5 Comparison of Accuracy

6.2 Observations

A given data set is trained using three algorithms k Nearest Neighbor, Naive Bayes and Support Vector Machine and their performance parameters are compared. It is observed that the algorithm K Nearest Neighbor gives better performance in all the classes ,at the same time maximum performance is obtained for SVM in class C, for the given data set.

Conclusion

The developed mobile application will capture Bluetooth signals sent from iBeacon and sent signal strength values to a server The server with the help of a localization algorithm finds the position and send location relevant information to the mobile .

Then classification algorithms are integrated into the system to predict the position in terms of building id. Three classification algorithms for this prediction are implemented and their performance parameters are evaluated. In recent years, there has been a great increase in the development of wireless technologies and location services. For this reason, numerous projects in the location field, have arisen. In addition, with the appearance of the open Android operating system, wireless technologies are being developed faster than ever.

Future Work

The optimal placement of beacons needs to be decided on a per-case basis .The scalability of the system should be considered since a large environment could have a detrimental effect on the positioning algorithm used. The k-NN algorithm for instance, considers every single fingerprint at runtime, which could lead to delays in the position estimation if the number of fingerprints is large. We can extend the estimation of position from building id to floor id and to room id level.

References

Xin-Yu Lin1, Te-Wei Ho1, Cheng-Chung Fang4, Zui-Shen Yen4, Bey-Jing Yang4, Feipei Lai1, *,2015,* A Mobile Indoor Positioning System Based on iBeacon Technology, *IEEE*

Pavel Kriz, FilipMaly, and Tomas Koze ,2016l, Improving Indoor Localization Using Bluetooth Low Energy Beacons, *Hindawi Publishing Corporation Mobile Information Systems* Volume 2016, , Article ID 2083094, 11 pages

Song Chai*, Renbo An and Zhengzhong D,2016An Indoor Positioning Algorithm Using Bluetooth Low Energy RSSI, *International Conference on Advanced Material Science and Environmental Engineering*

Ahmad Hatami and Kaveh Pahlavan,2005, A Comparative Performance Evaluation of RSS-Based Positioning Algorithms Used in WLAN Networks, *IEEE Communications Society* / WCNC 2005 0-7803-8966-2/05/$20.00 © 2005

Yankai Wang1, Qingyu Yang2, Guangrui Zhang3, Peng Zhang4, 2016, Indoor Positioning System Using Euclidean Distance Correction Algorithm with Bluetooth Low Energy Beacon *International Conference on Internet of Things and Applications (IOTA)* Maharashtra Institute of Technology, Pune, India 22 Jan - 24 Jan, 2016

Yu Gu_, Lianghu Quan_, Fuji Ren† and Jie , 2016, Optimal Parameter Setting for Indoor Localization via Big Data Analysis, *IEEE INFOCOM First International Workshop on Big Data Sciences, Technologies and Applications* (BDSTA 2016

Amira Chriki, Hatem Bettahar IResCoMath, Haifa Touati, Hatem Bettahar IResCoMath, Hichem Snoussi, Institut Charles Delaunay, SVM-Based Indoor Localization in Wireless Sensor Networks.

Wenzhe Zhang, Lei Wang, Zhenquan Qin, Xueshu Zheng, Liang Sun, Lei Shu Guangdong Petrochemical , 2014, INBS: An Improved Naive Bayes Simple Learning Approach for Accurate Indoor Localization, *IEEE ICC 2014 - Ad-hoc and Sensor Networking Symposium*

AnuradhaJayakody,ShashikaLokuliyana,DinushaChathurangi, DeminiVithana, 2016, Indoor Positioning: Novel Approach for Bluetooth Networks using RSSI Smoothing J.A.D.C *International Journal of Computer Applications* (0975 – 8887) Volume 137 – No.13, March 2016

Mario Muñoz -Organero and Claudia Brito-Pacheco, *2016,* Improving Accuracy and Simplifying Training in Fingerprinting-Based Indoor Location Algorithms at Room Level, *Hindawi Publishing Corporation Mobile Information Systems,* Volume 2016, Article ID 2682869, 16 pages http://dx.doi.org/10.1155/2016/2682869

Wissam Farjow, Abdellah Chehri*2, Mouftah Hussein*2, Xavier Fernando, *2011,* Support Vector Machines for Indoor Sensor Localization, *IEEE* 2011

Yuan Zhuang , Jun Yang , Longning Q and Naser El-Sheimy, Smartphone-Based Indoor Localization with Bluetooth Low Energy Beacons, *Sensors 2016*