Indoor Localization Based on the LoRa Technology

Rui Tian, HaiBo Ye(✉), and Li Sheng

Department of Computer Science and Technology, NanJing University of Aeronautics and Astronautics, Nanjing 210016, China
{tian2018,yhb,shengli}@nuaa.edu.cn

Abstract. In recent years, with the development of more advanced mobile technologies and wider application requirements, many new technologies have been used for indoor localization. In this paper, we design and implement an indoor localization system based on the LoRa wireless communication technology. We proposed an improved KNN based algorithm which can greatly reduce the size of the fingerprint database. The locating system is easy to deploy, it has good accuracy and low latency. Our field study showed that it can locate a moving object or user with the accuracy of 96.72%.

Keywords: Localization · Fingerprints · LoRa technology · KNN algorithm

1 Introduction

The indoor localization technology is one of the most important research areas of mobile computing. Especially in recent years, with the development of more advanced mobile technologies and wider application requirements, many new technologies have been used for indoor localization. The indoor localization technology can be used in many application scenarios, such as shopping malls, subway stations, parking lots and large factories, in which better localization performance are required to provide useful services. For example, scholars [18] uses Bluetooth devices to locate indoor shoppers, while scholars [6] uses WiFi devices to locate indoor people. In these scenarios, localization will face many challenges, such as the complex indoor structure and the effect of user movement. Different applications have different performance requirements, such as the accuracy, low latency, power efficiency and cost efficiency. Researchers are actively looking for solutions suitable for locating requirements.

Most existing localization solutions can be grouped into the following categories. 1. Indoor localization based on WiFi signal strength [9,10]; 2. Indoor localization based on Bluetooth [17,18,25]; 3. Indoor localization based on mobile detection [4]. However, they can't satisfy our requirements for the following reasons. The energy consumption of WiFi devices is comparatively large and the

M. Guan and Z. Na (Eds.): MLICOM 2020, LNICST 342, pp. 304–319, 2021.
https://doi.org/10.1007/978-3-030-66785-6_34

communication radius of Bluetooth also is short, they need more devices to fully cover a certain area, which is not cost efficient. The solutions based on mobile activity detection is cost efficient. However, they need complex training process and the error may accumulate which will affect the localizaiton accuracy. None of the above methods can fully meet our needs. We hope to provide a better localization solution.

Recently, The NB-IOT and LoRa technologies have attracted a lot of interest in the research area. They are representative wireless communication technologies of the IoT(Internet of Things). The comparison between LoRa and NB-IoT [5] shown that LoRa works in ISM frequency band, no authorization is needed to use LoRa communication. Meanwhile, LoRa has the characteristics of long distance and low power consumption. With NB-IOT, you can achieve high communication quality by using public mobile communication infrastructure. However, it cost more and is more vulnerable to attack. Therefore, we try to study whether the LoRa technology can be a potential solution for indoor localization.

This paper focuses on designing and implementing an indoor localization system of locating the equipment or people in a certain area. The requirements of the localization system are as follows: 1. Easy to deploy, which means the system can be quickly deployed and ready to work in a certain area. 2. Reasonable accuracy which can meet the requirements of the application. 3. Low cost and low power consumption, effectively reduce the energy consumption and cost of the system.

We will face some challenges to achieve these requirements for building such a localization system. The first is the implementation of the localization system, how to use it simply and quickly to obtain the location information in the scene. Second, the wireless signal of LoRa devices is not stable, which can be easily interfered and influenced by the changing environment. The last challenge is how to use low-cost and low-power equipment to realize the localization function, while allowing the equipment to work for a long period.

In order to achieve these challenges, LoRa technology and related equipment are used to achieve an indoor localization system. The system build a wide range of coverage and achieve better indoor localization accuracy. In this system, according to the character of LoRa signal, we process the collected data and achieve a better localization accuracy. Our work mainly includes the following contributions. First of all, we design and implement a localization system based on LoRa technology. The system can provide real-time location information of objects which carry the localization equipment. Secondly, we propose a KNN algorithm based on down sampling, which greatly reduced the size of the fingerprint database. The system predict the location of objects at the same time and it's accuracy and precision are acceptable. Finally, we do experiments in the actual scene, the experimental results show that our system can achieve an average accuracy of about 96.72%.

2 System Design

Figure 1 shows the structure of the system, including the hardware part and software part. The hardware includes the LoRaWan device and the LoRa node device; The software includes the MQTT server, the LoRa node software and data processing module. The LoRa node transmit the data to the LoRaWan device using the wireless signal. Then the LoRaWan device report it to the server. In the system, we design and implement the node device data handler, the gateway handler and the related server-side program management to calculate the location information.

The hardware is responsible for data collection. The LoRa node starts data transmission. The received data is then uploaded from the LoRaWan device to the server by MQTT protocol for data analysis on the server. On the server side, the pre-established fingerprint database is used to classify and predict the observed data and realize the positioning function. The LoRa node device is connected with the gateway device respectively and sends data to the server in the network through the gateway.

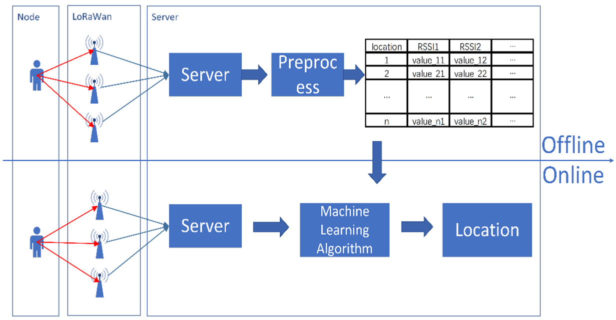


Fig. 1. System architecture

2.1 LoRa Technology

In free space, radio waves transmissions have no energy losses, but the energy density declines as space expands. The power of the receiver and sender has this characteristic and the formula is also known as the Friis free space equation.

$$P_R = P_T G_T G_R \left(\frac{\lambda}{4\pi d}\right)^2 \tag{1}$$

This equation describes the relationship between the transmitting power P_T (in dBw) of the wireless signal sender and the receiving power P_R (in dBw) of the wireless signal receiver in free space where G_T is the antenna gain of the transmitter, G_R is the antenna gain value of the receiver, λ is the working wavelength and d is the distance value [1].

The empirical model of path loss in indoor environment is presented by the existing research work [5].

$$PL(d) = PL(d_0) + 10nlog(\frac{d}{d_0}) + X_\delta \quad (2)$$

The formula shows the power relationship between sender and receiver; N is the path loss coefficient, d (in dB) is the distance between sender and receiver, and X_δ (in dB) is a white noise which subject to Gaussian distribution.

The first formula introduces the energy density changes with distance in free space without loss, and the second formula introduces the path loss model in real scene. Based on the above two models, we can find that for the wireless signal sender, the receiving signal strength of the receiver is different when the distance d from the sender is different, and this is the theoretical basis of our work in this paper.

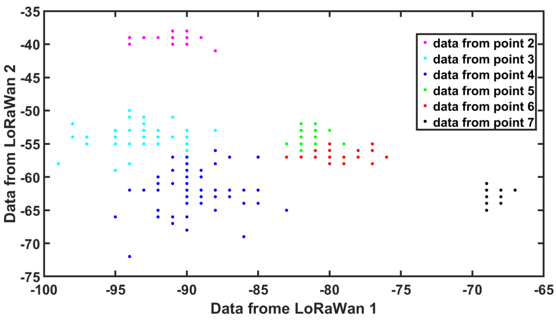


Fig. 2. RSSI values in different points

We use the LoRa equipment to test the variation of LoRa signal strength with distance in indoor environment. We collected a number of data at different points and plotted them. As can be seen from Fig. 2, the RSSI values fall in a zone for a certain point.

As mentioned in [6], the change of RSSI (Received Signal Strength Indication, RSSI) value can be divided into two types: temporal change (the value of RSSI at the fixed point may fluctuate) and spatial change (the value of RSSI changes with the change of equipment position). We can see the third and fourth points from Fig. 3 that the signal intensity is significantly lower than the model value. The reason is that the experimental site is located at the intersection of corridors. When the distance become larger than 50 m, the device begins to be affected by another corridor. In general, the signal strength of the device decreases with the increase of distance. In the indoor environment, RSSI value decreases with distance but the relationships are more complicated.

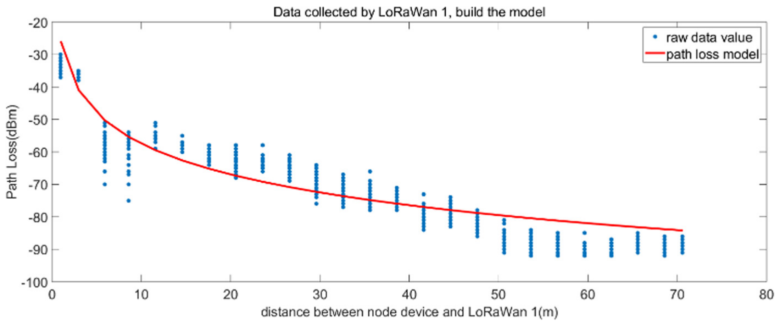


Fig. 3. RSSI value changes with different distance between LoRa node and LoRaWan

2.2 Generate the FingerPrints

The generation of fingerprint database refers to the establishment of fingerprint database in this area by collecting data in the offline stage and the signal intensity value of multiple gateways at each point.

First, we introduce the format of the data. As shown in Table 1 and Table 2, the data format 1 refers to the data transmission form from LoRa node device to LoRaWan device. The data format 2 refers to the data transmission form from LoRaWan device to the server. The node device first transmits the data signal to the LoRaWan. The LoRaWan records the node information and the received signal strength. After that, the LoRaWan reports the received data to the server. In this way, the system send data from the node to the server.

Table 1. Data format 1

Node Device ID	Node Device Time

Table 2. Data format 2

LoRaWan Device ID	LoRaWan Device Time	Node Device ID	Node Device Time	RSSI value

Secondly, we need to preprocess the data collected by the server. First, we try to do smoothing of the data from each gateway. The optional solutions are as follows: 1) the sliding average method, 2) the exponential sliding average method and 3) the SG filtering method. Here, we make use of the quadratic exponential smoothing. For a sequence X(1), X (2), ..., X (n), the formula for the first smoothing is

$$S^1(t+1) = aX(t) + (1-a)S^1(t) \tag{3}$$

where a is the smoothing coefficient. Then, the second smoothing is based on the first smoothing, as shown in the following formula:

$$S^2(t+1) = aS^1(t) + (1-a)S^2(t) \tag{4}$$

Based on the two formulas above, we can get X′(t+T), where

$$X'(t+T) = 2S^1(t) - S^2(t) + (\frac{a}{1-a})(S^1(t) - S^2(t)) \tag{5}$$

After smoothing, we get more clean data.

Furthermore, the LoRa communications are unreliable. In the process of establishing fingerprint database, some error message exits. For example, some data is received by LoRaWan A but not by LoRaWan B. Easy to exist if the device does not transmit information continuously, then the device may be disconnected, this part of the data should be removed. For discontinuous data, a packet propagation error may result in data loss at a LoRaWan. In this case, we use a fitting method to fill in the missing value. In this way, we increase the volume of samples.

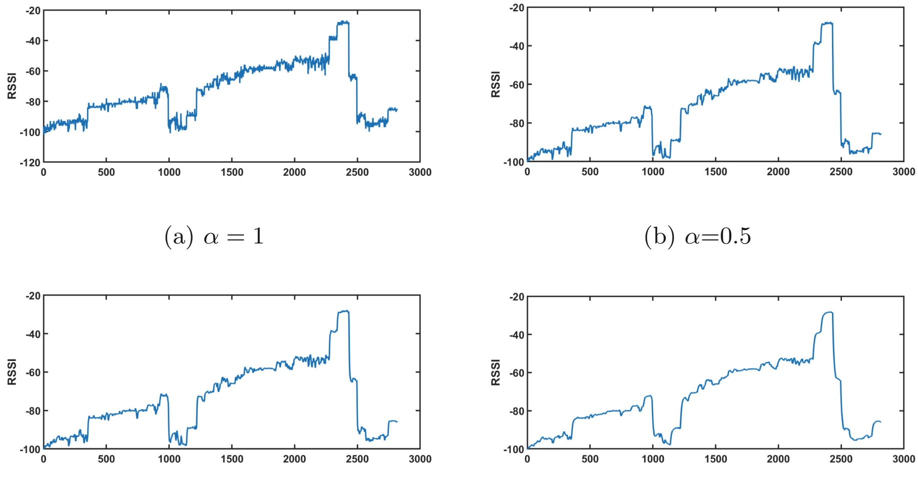
Algorithm 1. Smooth algorithm

Input: *collected*(RSSI_1, RSSI_2, RSSI_3, POINT)
Output: *smoothed*(RSSI_1', RSSI_2', RSSI_3', POINT)

let $s\_1 := \{\}$, $s\_2 := \{\}$
let $a := 0.6$
let $lenC$:= the length of *collected*
for $i := 1$ to $lenC$ **do**
  $s\_1(1,i) := a * data(i,1) + (1-a) * data(i-1,1)$
for $i := 2$ to $lenC$ **do**
  $s\_2(1,i) := a * s\_1(i,1) + (1-a) * s\_1(i-1,1)$
let $smoothed := \{\}$
for $i := 2$ to $lenC$ **do**
  $smoothed(1,i) := 2s\_1(1,i) - s\_2(1,i) + a/(1-a) * (s\_1(1,i) - s\_2(1,i))$
return *smoothed*

After processing the data, we get the RSSI values of three LoRaWan during the node device moving. Each LoRaWan Device give the observations of the node device. These observations comprise the fingerprint database. At a random moment, a record or an observation is composed of RSSI values from three LoRaWans. With the search and comparison of data in fingerprint database, the location of the device can be predicted (Fig. 4).

Some researchers have studied the method to dynamically adjustment fingerprint database [3]. Based on their conclusion, the dynamic adjustment algorithm



(a) $\alpha = 1$ (b) α=0.5

(c) $\alpha = 0.3$ (d) $\alpha = 0.1$

Fig. 4. Smoothed data

can improve the accuracy of the locating system. The initial setting of fingerprint database may not be effective all the time, specially when the environment changed. Further more, during the locating process, a user can manually correct the location information by a mobile phone interface application.

2.3 Localization Algorithm

After data collection and data preprocession, the fingerprint database is created. On the basis of fingerprint database, KNN algorithm is used to realize the localization function.

To locate the objects, the first problem is the imbalanced data. The possible methods for the problem include: 1. Up-sampling, the way is to increase the number of samples of each class, let the amount of each class to be same; 2. Down-sample, which is to reduce the sample size of each class, let the amount of each class to be same; 3. Weight the data, it gives different weight to different sample. We choose the down-sample to solve the problem.

KNN algorithm have some drawbacks. When the number of sampling points is too huge, it will increase the calculation of KNN algorithm. It's also a huge work to do site survey in real scene. To deal with this problem, the system make use of the down-sample based method. According to the number of samples collected at each point (total of n points), we choose m samples in each point. Therefore $n * m$ records are obtained. These records constitute the fingerprint database.

Through the above process, we obtain a balanced data set, which is referred as the fingerprint database. Then KNN algorithm is used to do classification.

The theoretical basis of KNN algorithm is described below. Suppose we have a data set containing N points, C_k for category, with N_k, hence the $\sum N_i = N$. If a certain point needs to be predicted, K points closest to that point are obtained. If K points belong to C_k, there are

$$p(x|C_k) = \frac{K_k}{N_k} \tag{6}$$

Similarly, in the unconditional case

$$p(x) = \frac{K}{N} \tag{7}$$

The prior probability of the class is

$$p(C_k) = \frac{N_k}{N} \tag{8}$$

Combining the above three equations, we get the posterior probability formula of the category according to bayes' law.

$$p(C_k|x) = \frac{p(x|C_k)p(C_k)}{p(x)} = \frac{K_k}{K} \tag{9}$$

The pseudo code of KNN is shown below.

Algorithm 2. KNN algorithm

Input: labeled data $labd(data, label)$
data to be predicted $pred(data)$
Output: $pred(data, label)$

```
1: let knn_k := k
2: for i := 1 to labd.length do
3:     calculate the nearest knn_k points for pred(i, :) in labd(data, label)
4:     count the knn_k points according to it's label, generate result
5:     label of pred(i, :) := the label of max num of result
6: return pred(data, label)
```

3 Experiment

3.1 Experiment Setting

First, we need to set the parameters of the wireless communication device before use. There are mainly the following five parameters: the spread spectrum factor, the transmitting power, the bandwidth, the coding rate and the wireless signal frequency.

1) The Spread spectrum factor. When other parameters are fixed, the bit rate of the device is fixed. The larger the spread-spectrum factor is, the lower the actual data transmission rate is.
2) Under the same conditions, the greater the transmitting power, the farther the transmission distance under the same conditions.
3) The smaller bandwidth, the longer transmission distance. However, when the bandwidth is too small, the probability that the device with low receiving sensitivity will not receive data increases.
4) The coding rate represents the proportion of useful information in the information.
5) The lower the wireless signal frequency, the better the signal penetration.

We choose the Arduino board as the basic platform and connect LoRa chip (SX1276/8) to the board to realize LoRa transmission. The system adopts Dragino LG-01s as LoRaWan Device. The device contains of Arduino Yun and LoRa chip. We set the same parameters in devices so that they can translate the message with each other.

3.2 Experiment Scenario

The LoRa network topology is a star shape. During the experiment, the process is to first send data from the LoRa node device to the LoRaWan device. The LoRaWan device get the received signal strength and some other important data. After that, the data will be transmitted to the server by the TCP/IP protocol. In our experiment, we totally set up three LoRaWan devices and one node device. The node device sends two data samples per second. The LoRaWan sends the data from the node device to the remote server. The layout of the experimental site is shown in Fig. 5. This is the first floor plan in a building. During the experiment, there may exist a small number of people walking by.

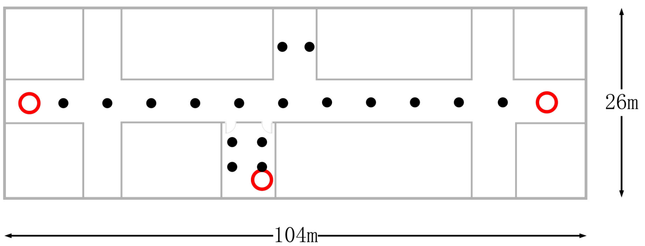


Fig. 5. The structure of the build

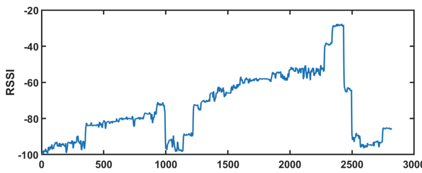
The node device can generate a device independent time. It is pushed to the MQTT server through the MQTT protocol. Then MQTT server saves and processes the data records.

3.3 Data Setting

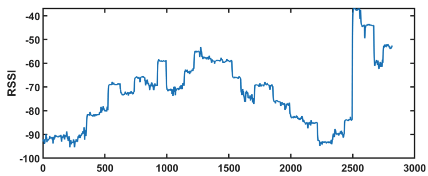
By carrying the experiment and processing the collected data, we obtain the most important part of the location algorithm: the fingerprint database. An example of the fingerprint library is shown in Fig. 6. The first column is the time of node device, the last column is the label of location and the rest are the received signal strength of the LoRaWan devices.

1	2	3	4	5
262827	-100	-93	-32	1
265350	-100	-92	-31	1
266190	-99	-92	-32	1
267032	-99	-92	-32	1
269554	-96	-93	-32	1
272077	-100	-96	-32	1
282168	-99	-89	-32	1

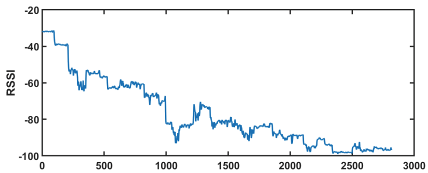
Fig. 6. The collected data



(a) Data from LoRaWan 1



(b) Data from LoRaWan 2



(c) Data from LoRaWan 3

Fig. 7. Smoothed data

Figure 7a, Fig. 7b and Fig. 7c show the RSSI value with the node device moving. It is worth noting that at the last four points, the RSSI values of LoRaWan 1 and LoRaWan 2 have changed significantly, but the RSSI value of LoRaWan three devices has not changed much. This is because the LoRaWan device and the node device are too far away, the RSSI values is attenuated, and the effect of the movement of the location on the RSSI values begins to slow down. We use drawing tools to depict the collected data in three-dimensional coordinates. Each dimension represent a LoRaWan device. For different locations, the collected data are relatively independent to each other in Fig. 8.

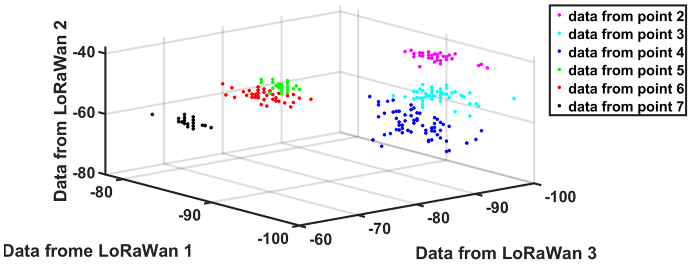


Fig. 8. Data in 3 dimension

4 Evaluation

4.1 Accuracy

In order to evaluate the accuracy of localization, we try using different machine learning algorithm for localization. We use SVM (Support Vector Machine, SVM), Cart decision tree, KNN (k nearest neighbor, KNN) and ensemble learning methods to train the model. In the initial state, using the data obtained from the measurement, the localization results are shown in the Table 3. Indoor localization using KNN methods can achieve promising accuracy.

Table 3. The accuracy of different methods.

Method	Wrong	Right	Accuracy
KNN (k = 13)	14	486	97.20%
SVM	19	481	96.20%
Cart Tree	32	468	93.60%
Ensemble	19	481	96.20%

Based on the existing data, the accuracy of the KNN localization results obtained under different k values is shown in Fig. 9. The KNN algorithm needs to calculate the distance from each point, so the calculation amount of the algorithm will increase with the increase of samples. In practical scenarios, the relationship between the amount of calculation and accuracy should be measured. Figure 10 show the CDF (cumulative distribution Function, CDF) curve of different methods.

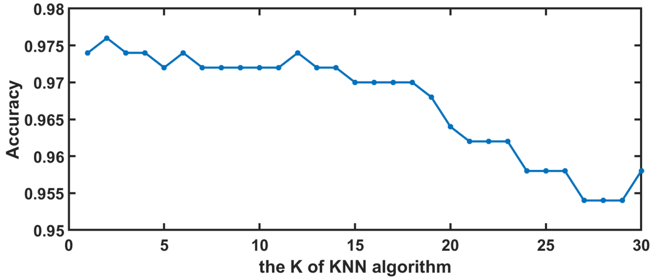


Fig. 9. Accuracy of different K values

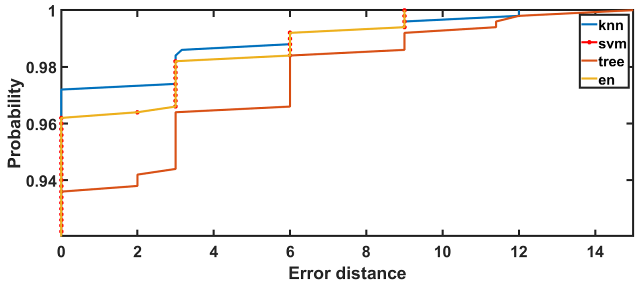


Fig. 10. CDF curve of different methods

4.2 System Deployment

During the deployment phase, we install the LoRaWan device and connect it to the Internet. Meanwhile, a server with public network IP is responsible for location calculation and recording. When the locator device appears in the system area, LoRaWan establishes a connection to the device, collects the signal strength information from the device and sends it to the server. The system supports a simple and quick deployment.

The system has two steps to achieve localization: offline pre-training and online prediction to achieve the localization function. The offline pre-training (fingerprint library method) is time-consuming which requires dividing the whole system area into grids and measuring the representative fingerprint within the grid. The online prediction is real-time. The system obtains the real-time records of the node device and use KNN algorithm to get the location point.

To test the location calculation delay of the algorithm under different data volumes, we used the collected data for evaluation. Suppose the initial data volume is t, where t_1 is the number of records in the fingerprint database and t_2 is the number of records to be predicted, satisfying $t = t_1 + t_2$. The following figure shows the time spent to complete the corresponding data volume ($t = 2817$). As can be seen from the Fig. 12, the Cart Decision Tree method takes less time, and the KNN algorithm is only as effective as the Cart Tree under the data volume of $10 * t$ (Fig. 11).

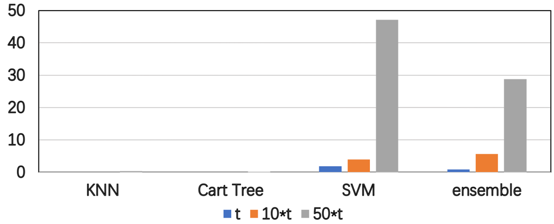


Fig. 11. Time of train and predict

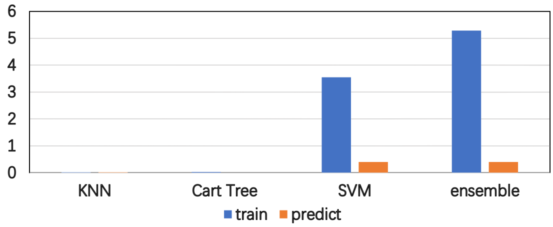


Fig. 12. Time consuming in same condition

We give the comparison of four methods under $10 * t$ data volume in Fig. 12. Where KNN algorithm doesn't need a learning process, it is meaningless to consider its model training. It can be seen that both SVM and ensemble methods require training classifier, and their training time is relatively long. Meanwhile, KNN and Cart Tree perform better in time.

5 Related Work

Indoor localization has been studied for several years. Here, we provide a brief introduction to related work in this field.

First is the emergence of Lora technology. Scholars began to study the characteristics of wireless communication technology Lora. Lora means long range and long distance. By using modulation and demodulation technology, long-distance data transmission is realized. Researchers [2,3] studied the distance characteristics of Lora in outdoor open space. [2] provides a simple introduction of Lora technology and how to establish an outdoor environment for experimental conditions. At the same time, it points out that when the Fresnel region between the transmitting device and the receiving device can have more than 60% of the visible region, the signal transmission is the best. [3] introduces some related contents of Lora protocol and the parameters of Lora equipment. The technical characteristics and reliability of Lora were studied [5,14,19].

The second is the field of indoor localization. There are classic radar localization system and Horus system to use WiFi for localization. The latter studies the change of RSSI signal in space and time, realized high-precision localization with WiFi device, deployed multiple gateway devices in the room, designed a system to locate the device, the effect is very good. The mobile air pressure sensor [14] is used to locate the mobile floor, and the signal characteristics of Lora enable it to locate the floor. A localization system is established by using WiFi device, and the fingerprint database is used to match the offline map for localization [9,10]. In addition, many researchers study the use of different detection methods for indoor localization, such as the use of low-power Bluetooth devices [17,18,25], light [23], sound [12] for indoor localization. Scholars [4] use multiple WiFi devices to study the data collection of heterogeneous devices and how to dynamically adjust the fingerprint database to achieve better accuracy and robustness. At present, the hot research in the field of location includes: using fingerprint signal to detect indoor and outdoor alternate areas [30,31], improving the accuracy of location by testing mobility [24] and using the combination of mobile phone sensor and GPS localization to realize localization and tracking in special scenes [16,25].

With the development of technology, there are many new application scenarios for localization, and many new requirements appear under these application scenarios. The research work of relevant aspects includes: 1. Using the changes of indoor environment signals to carry out indoor localization and action perception under the condition of non marking [7]; 2. Military applications, research on underwater and air localization technology; 3. Detection of human heart rate information using WiFi equipment [21]; localization between micro air vehicles [22].

6 Conclusion

In this paper, we proposed a new approach for indoor localizaiton based on the LoRa technology. We first study to signal characteristics of the LoRaWan in the indoor environment and find that it is possible to use the LoRa technology for indoor localizaiton. Then, we established the fingerprint database and proposed an improved KNN based algorithm which can greatly reduce the size of the fingerprint database. After that, we proposed our field study and the result show that the system performance is good enough for our requirements. We also find that the user movement in the indoor environment can affect the LoRa signal strength. Based on this feature, in the future work, we will focus on device free indoor localization based on the LoRa technology.

References

1. Aref, M., Sikora, A.: Free space range measurements with Semtech LoRa™ technology. In: 2014 2nd International Symposium on Wireless Systems within the Conferences on Intelligent Data Acquisition and Advanced Computing Systems, pp. 19–23. IEEE (2014)
2. Lavric, A., Popa, V.: Internet of things and LoRa™ low-power wide-area networks: a survey. In: 2017 International Symposium on Signals, Circuits and Systems (ISSCS), pp. 1–5. IEEE (2017)

3. Sinha, R.S., Wei, Y., Hwang, S.H.: A survey on LPWA technology: LoRa and NB-IoT. ICT Express **3**(1), 14–21 (2017)
4. Wang, H., Sen, S., Elgohary, A., et al.: No need to war-drive: unsupervised indoor localization. In: Proceedings of the 10th International Conference on Mobile Systems, Applications, and Services, pp. 197–210. ACM (2012)
5. Xu, W., Kim, J.Y., Huang, W., et al.: Measurement, characterization and modeling of LoRa technology in multi-floor buildings. IEEE Internet Things J. **7**(1), 298–310 (2019)
6. Youssef, M., Agrawala, A.: The Horus location determination system. Wireless Netw. **14**(3), 357–374 (2008)
7. Paul, A.S., Wan, E.A., Adenwala, F., et al.: MobileRF: a robust device-free tracking system based on a hybrid neural network HMM classifier. In: Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing, pp. 159–170. ACM (2014)
8. Rai, A., Chintalapudi, K.K., Padmanabhan, V.N., et al.: Zee: zero-effort crowdsourcing for indoor localization. In: Proceedings of the 18th Annual International Conference on Mobile Computing and Networking, pp. 293–304. ACM (2012)
9. Wu, C., Yang, Z., Liu, Y.: Smartphones based crowdsourcing for indoor localization. IEEE Trans. Mob. Comput. **14**(2), 444–457 (2014)
10. Wu, C., Yang, Z., Liu, Y., et al.: WILL: wireless indoor localization without site survey. IEEE Trans. Parallel. Distrib. Syst. **24**(4), 839–848 (2012)
11. Yang, S., Dessai, P., Verma, M., et al.: FreeLoc: calibration-free crowdsourced indoor localization. In: 2013 Proceedings IEEE INFOCOM, pp. 2481–2489. IEEE (2013)
12. Machhamer, R., Dziubany, M., Czenkusch, L., et al.: Online offline learning for sound-based indoor localization using low-cost hardware. IEEE Access **7**, 155088–155106 (2019)
13. Yu, J., Na, Z., Liu, X., et al.: WiFi/PDR-integrated indoor localization using unconstrained smartphones. EURASIP J. Wireless Commun. Netw. **2019**(1), 41 (2019)
14. Ye, H., Gu, T., Tao, X., et al.: Scalable floor localization using barometer on smartphone. Wireless Commun. Mob. Comput. **16**(16), 2557–2571 (2016)
15. Liando, J.C., Gamage, A., Tengourtius, A.W., et al.: Known and unknown facts of LoRa: experiences from a large-scale measurement study. ACM Trans. Sens. Netw. (TOSN) **15**(2), 1–35 (2019)
16. Augustin, A., Yi, J., Clausen, T., et al.: A study of LoRa: long range & low power networks for the internet of things. Sensors **16**(9), 1466 (2016)
17. Hou, X., Arslan, T.: Monte Carlo localization algorithm for indoor positioning using Bluetooth low energy devices. In: 2017 International Conference on Localization and GNSS (ICL-GNSS), pp. 1–6. IEEE (2017)
18. Dickinson, P., Cielniak, G., Szymanezyk, O., et al.: Indoor positioning of shoppers using a network of Bluetooth low energy beacons. In: 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–8. IEEE (2016)
19. Cattani, M., Boano, C.A., Römer, K.: An experimental evaluation of the reliability of LoRa long-range low-power wireless communication. J. Sens. Actuator Netw. **6**(2), 7 (2017)
20. Ye, H., Yang, W., Yao, Y., et al.: BTrack: using barometer for energy efficient location tracking on mountain roads. IEEE Access **6**, 66998–67009 (2018)

21. Khamis, A., Chou, C.T., Kusy, B., et al.: CardioFi: enabling heart rate monitoring on unmodified COTS WiFi devices. In: Proceedings of the 15th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services, pp. 97–106 (2018)
22. van der Helm, S., Coppola, M., McGuire, K.N., et al.: On-board range-based relative localization for micro air vehicles in indoor leader-follower flight. Auton. Robot. **44**, 1–27 (2019)
23. Zhang, H., Cui, J., Feng, L., et al.: High-precision indoor visible light positioning using deep neural network based on the Bayesian regularization with sparse training point. IEEE Photonics J. **11**(3), 1–10 (2019)
24. Carlino, L., Bandiera, F., Coluccia, A., et al.: Improving localization by testing mobility. IEEE Trans. Signal Process. **67**(13), 3412–3423 (2019)
25. Hou, X., Arslan, T., Juri, A., et al.: Indoor localization for Bluetooth low energy devices using weighted off-set triangulation algorithm. ION-GNSS **2016**, 2286–2292 (2016)
26. Chintalapudi, K., Padmanabha Iyer, A., Padmanabhan, V.N.: Indoor localization without the pain. In: Proceedings of the Sixteenth Annual International Conference on Mobile Computing and Networking, pp. 173–184. ACM (2010)
27. He, S., Chan, S.H.G.: INTRI: contour-based trilateration for indoor fingerprint-based localization. IEEE Trans. Mob. Comput. **16**(6), 1676–1690 (2016)
28. Jiang, Y., Li, Z., Wang, J.: PTrack: enhancing the applicability of pedestrian tracking with wearables. IEEE Trans. Mob. Comput. **18**(2), 431–443 (2018)
29. Zhang, L., Liu, J., Jiang, H., et al.: SensTrack: energy-efficient location tracking with smartphone sensors. IEEE Sens. J. **13**(10), 3775–3784 (2013)
30. Shtar, G., Shapira, B., Rokach, L.: Clustering Wi-Fi fingerprints for indoor-outdoor detection. Wireless Netw. **25**(3), 1341–1359 (2019)
31. Chow, K.H., He, S., Tan, J., et al.: Efficient locality classification for indoor fingerprint-based systems. IEEE Trans. Mob. Comput. **18**(2), 290–304 (2018)