RETaIL: A Machine Learning-Based Item-Level Localization System in Retail Environment

Xiaoyi Xu[1(✉)], Xiaoming Chen[1], Jiang Ji[1], Feng Chen[1], and Addicam V. Sanjay[2]

[1] Intel Asia-Pacific Research and Development Ltd., Shanghai, People's Republic of China
{xiaoyi.xu, xiaoming.chen, jiang.ji, andy.chen}@intel.com

[2] Intel, Chandler, AZ, USA
addicam.v.sanjay@intel.com

Abstract. Radio-frequency identification (RFID) technology has become the key focus of indoor localization recently. The low cost and flexibility allow numbers of passive RFID-based algorithms been proposed for indoor localization. However, in a real-world environment including retail store and supermarket with large-scale item-level deployment of RFID tags and complex surroundings, these algorithms may not be available due to the collision and interference. Existing algorithms either require extra hardware or only take a small number of tags into consideration, facing difficulty in applying to these places. In this paper, we propose a novel machine learning-based REal-Time and Item-Level (RETaIL) indoor localization system, which is designed to tolerate various interference. RETaIL incorporates three machine learning algorithm, J48, SVM and cloth grouping, for indoor localization. Validations in both complex laboratory environment and real-world Levis outlet store demonstrate the accuracy and efficiency of RETaIL and its capability of dealing with interference in retail environment.

Keywords: Passive RFID · Machine learning · Item-level localization Retail environment

1 Introduction

Embedded sensors are changing the way people live and retailers manage merchandise. As one of the sensor technologies, radio-frequency identification (RFID) technology is attracting growing interests in various applications [1], and its wider adoption defined the revolution of the Internet of Things. With the desirable features of cost-effective, contactless communications, high data rate and easy implementation, item-level deployment of RFID technology is applied in warehouse, supermarket, retail store and factories [2]. During the past decades, item-level RFID offered tangible benefits to both suppliers and retailers [3, 4] in product tracking, supply chain, anti-counterfeiting and stock estimation. However, there are still losses caused by unsolved problems including

I. Romdhani et al. (Eds.): CollaborateCom 2017, LNICST 252, pp. 221–231, 2018.
https://doi.org/10.1007/978-3-030-00916-8_21

misplaced items, out-of-stock items and inventory shrinkage, which make RFID technology-based real-time item-level localization urgently needed in retail environment.

Compared with the relative simple environment that most indoor localization implemented in, including dense tag environment [5] and clutter environment [6], retail store or warehouse environment is much more complicate. The main challenges of applying indoor localization algorithm in retail environment lay in: (1) thousands of RFID tags may be densely deployed in a small area; (2) several RFID readers may be deployed within the range of backscattered signal that tags send back; (3) different materials of shelves, walls and other obstacles may exist; (4) costumers may cover or touch the tags or move around in the room all the time. Under such circumstances, the signals among RFID tags and readers can be greatly altered by interference of tag-tag collisions, reader-reader collision, signal reflections of different surfaces as well as other environment factor including human activities, temperature, noise and humidity.

In this paper, we propose a novel item-level localization system that focuses on retail environment by combining three efficient machine learning algorithms, Support Vector Machine, J48 and a novel algorithm named cloth grouping. The proposed system can make use of various information and its performance is robust to challenges from real-world store with thousands of items and crowded customers moving around. Based on Intel® Retail Sensor Platform we offer a simple way for retailers to locate products of interest efficiently and accurately, and eventually reduce losses from misplaced or out-of-stock items.

The rest of the paper is organized as follows: in Sect. 2, we present a brief review of related work in the field of RFID localization and machine learning algorithms that applied in RFID-based problems. Section 3 introduces the proposed localization system RETaIL, including the detailed feature description and algorithm description. In Sect. 4, after tested RETaIL in lab environment, we turn to practical application in Levis outlet store for further evaluation. Finally, we briefly conclude our work in Sect. 5.

2 Relation to Prior Work

A variety of indoor localization algorithms have been proposed in last decades using RFID technology including active RFID-based localization algorithms [7–9, 20] and passive RFID-based algorithms [2, 5, 10]. The cost-efficient nature of passive RDIF enabled large-scale deployment of embedded RFID tags and created many dense tag environments. Due to the fact that passive RFID tags are easily interfered by dense tags and dense readers, algorithms were proposed to solve the tag collision and reader collision problems [11] in dense RFID environments [5, 12–15, 20]. However, most of these algorithms are proposed and tested in a relatively simple environment. For example, in Zhang's work [2], the dense environment has only 16 tags/m^2. InPLaCE [6] system is proposed to deal with clutter environment, but there are less than 50 tags for testing. Performing item-level indoor localization in a complex environment is still a challenging task.

In terms of prediction approach, besides math-physics-based methods, machine learning algorithms were also applied in RFID-based problems. For example, Li [16] extracted read rate, phase and RSSI features to distinguish human-object interaction including still, translation, rotation, swipe and cover touch using several 2-class SVMs. Later, they also proposed a machine learning pipeline named PaperID [17] to distinguish multiple simultaneous gestures over RFID tag by incorporating SVM with similar features. Machine learning algorithms achieve good classification performance based on RFID parameters, which provide insights into RFID technology-based problem including indoor localization.

3 System Framework

In this paper, we developed a novel localization system with the purpose of locating the items with RFID tags in a retail environment. The deployment of the RFID system is as follow: a large number of clothes that are densely placed in different areas are embedded with RFID tags. Several RFID readers are deployed in the room, which will send energy to RFID tag, and read the received signal information, including RSSI, frequency and phase from tags. Based on these setting, localization system is developed by incorporating machine learning algorithms and the data collected from readers.

Figure 1 shows the framework of RETaIL, including data collection stage, feature extraction stage, prediction stage, voting stage to output the final location based on the results from multiple algorithms.

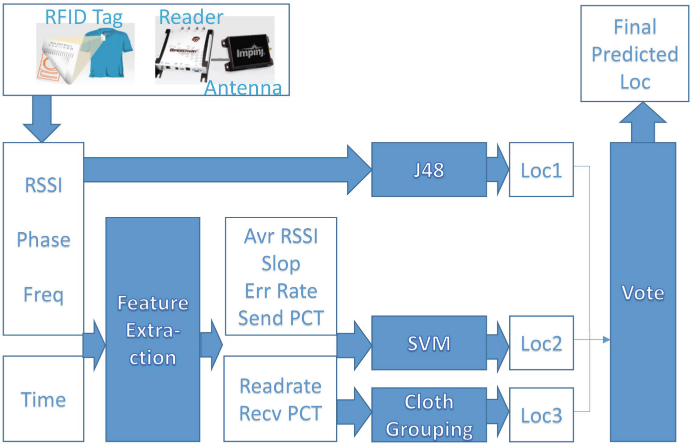

Fig. 1. Overview of system framework.

3.1 Feature Extraction

For the three algorithms we adopted in this system, different information is used with respect to the function of each algorithm. Here, RF channel parameter including frequency, RF phase, RSSI, as well as corresponding reader IDs are used to build model.

Besides, as each tag might get read by multiple readers more than once in a given period of time, a sliding window (window size = T) which slides every T/2 with 50% overlap is utilized to segment the RF channel parameters reported by each reader. For each segment, seven features are derived from RSSI, RF phase, frequency and time.

Average RSSI Value. Passive RFID tags operate by reflecting the RF signal transmitted to them from a reader and RSSI is a measurement of reflected signal. In the retail environment, RFID tags are densely deployed within limited area, in which the signals among tags and readers can be greatly altered by interference of RFID tag collisions, reader-reader collisions as well as the environment factor, making uncontrolled RSSI values can't reflect accurate information. However, by keeping the maximum power level, we can utilize the average RSSI values that each reader received from a tag within segments as features [17], which makes an n-dimension feature vector.

RFID tags can receive signals only in a short distance, so usually a tag can mainly receive signal from several readers around it. Besides, signal-sending rates of all readers are adjusted to be distinct from each other, which makes read rate information effective for classification. The definitions are as follow:

Tag Read Rate. The tag read rate is defined as the number of packets received from each tag by each reader per second.

Sent Percentage. For each RFID reader, sent percentage is defined as the ratio between number of packets received from one tag and number of all packets received by this reader (Eq. (1)).

$$SP_{i,j} = \frac{\sum_a \sum_b \theta_{ab}}{\sum_b \theta_b}, \theta = 1 \ if \ a \in tag_i, b \in reader_j. \tag{1}$$

Receive Percentage. For each tag, receive percentage is defined as the ratio between number of packets received by one reader and number of all packets received from this tag by all readers.

$$RP_{i,j} = \frac{\sum_a \sum_b \theta_{ab}}{\sum_a \theta_a}, \theta = 1 \ if \ a \in tag_i, b \in reader_j. \tag{2}$$

Phase and frequency wrap around between 0–3.14 and 902–928 MHz and repeat recurrently. Ideally, when having X axis as frequency and Y axis as phase, a series of parallel lines could be obtained. As mentioned above, with a sliding window of T minutes with 50% of overlap, we get the phase/frequency ratio over one of these parallel lines instead of doing line fitting. In the end we took the average of this sliding window period as feature. RF parameters phases and frequencies are utilized to compute slope and error rate as follow:

Slope. It's the slope of the graph when phase values were plotted against frequency.

$$slope = \frac{\left(\sum_{t=0}^{T} frequency \times \sum_{t=0}^{T} phase\right) - count \times \sum_{t=0}^{T} frequence \times phase}{\left(\sum_{t=0}^{T} frequency\right)^2 - count \times \sum_{t=0}^{T} frequency^2}. \quad (3)$$

Error Rate. Due to the interference, signals may vary from time to time and error rate is an estimation of the fluctuation of phase and frequency. In (4), t is between $(n - 1)T/2$ and $n * T/2$, denoting the nth slide window.

$$error\ rate = \frac{\max(phase_t)}{\min(frequency_t)} - \frac{\min(phase_t)}{\max(frequency_t)}. \quad (4)$$

Finally, for n readers, average RSSI value, tag read rate, sent percentage, receive percentage, slope and error rate are calculated and encoded into n-dimension features according which reader receives these signals, respectively.

3.2 Machine Learning Algorithms

The model we propose is a machine learning model instead of a math-physics based model because signal strength is not a directly indicative of distance in the case of retail environment with disorganized interference, obstruction and collision. Furthermore, our early stage experiments show that although count of reader reads are good indicative of distance, only using the read rate was not giving stable results. Therefore, we took a slightly different approach by using a voting mechanism between two supervised machine learning models and one unsupervised machine learning model

J48. For each tag, more than one signals are received by different readers within a period, each signal reflects the characteristics of the tag. As a powerful approaches to discover useful patterns from large and complex bulk of data, J48 [18] is used to make full use of all these signals. Reader information, RSSI, frequency and phase are used as independent features and each signal is treated as a sample to perform multi-label classification. Pre-trained model are used to predict locations for each sample of a tag. Finally, the location with highest voting score is selected.

SVM. We implement optimized LIBSVM [19] with RBF kernel and tuned parameters and use SVM as a multi-class classifier in this project. To overcome the unbalanced numbers of samples in each location, weight parameter w is set to be inversely proportional to the number of samples for each class. Prior to location prediction, exhaustive feature selection algorithm is use to try every combinations of the six kinds of features described in Sect. 3.1. To ensure robustness of model, we use training datasets of different size to perform feature selection process and then validate the accuracy of the constructed model. Finally a feature subset that obtained the highest accuracies is selected to construct SVM model. At deployment stage, same feature set and scale range is used for query data.

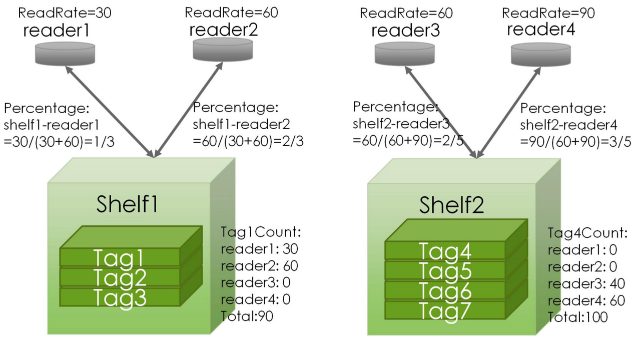

Fig. 2. Illustration of cloth grouping algorithm. Left panel matches criteria 1 and tight panel matches criteria 2.

Cloth Grouping. In this system, read rate of every reader is specially adjusted to be different from each other. System compares the read rate of every tag by every reader with pre-stored read rate of every shelf. A tag is predicted to be located in one shelf when it meets one of the following criteria: (1) read rate of a tag is close to read rate of a shelf; or (2) percentage of shelf-reader is close to percentage of tag-reader (as shown in Fig. 2).

Voting Strategy and Optimization. For J48 and SVM, multiple signals are received from one tag and each signal is used for prediction, a voting process is used to decided prediction result for each tag. After prediction results are obtained from each algorithms, a voting strategy is utilized to decide the final location of an item. Specially, if three different locations are predicted for an item by three algorithms, after validations and tests, we found that simply ignore cloth grouping result and compare the confidence of the J48 and SVM and take the result of the algorithm with higher prediction confidence as the final result gives good accuracies.

To implement real-time localization system, the following optimization approaches are utilized to improve efficiency while retaining high accuracy: (1): For the three supervised algorithms, parallelized computing is enabled; (2): Sliding window size T = 2 min is defined to have a better tradeoff between size of training data and efficiency; (3): For the most time consuming algorithm, SVM, a novel implementation is developed to compress model and multi-thread is used to decrease computing time, detailed engineering implementation of the speedup library is not described as it is less relevant to this study.

4 Experiments

This section outlines the details related to deployment of both the laboratory and real retail store and evaluate proposed approach towards attaining the end objective of determining item location inside a retail environment.

4.1 Experiment Results on Lab Environment

To evaluate how machine learning algorithms helps in dealing with interference for item-level localization, we setup a laboratory with dimensions of 27 foot * 27 foot to imitate retail environment. Considering that a real store would have a dense population of tags, we had brought in shelves and racks and populated them with of real clothing with respect to the lab deployment. The passive RFID deployment is based on Intel Retail Sensor Platform and the layout is shown in Fig. 3. In Fig. 3, the gray portions are either walls, desks, lab shelves, or areas where items cannot be placed. The light blue rectangles designate the shelves of our “store” with tagged jeans, which are the targets that will be used to evaluate their predict locations. Rectangles A/D designate the wooden furniture and H/I are metal racks that are deployed among shelves to imitate real store and to increase interference and multipath effect. The black squares represent the RFID readers, which are approximately 100 in. up from the floor. Totally 730 jeans are distributed in shelves with uneven numbers for evaluation and researchers movements are also included to imitate real store.

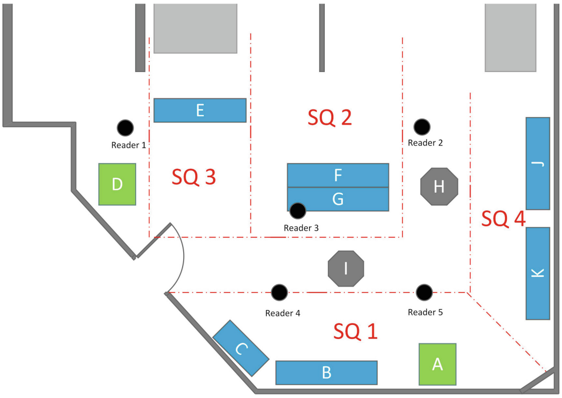

Fig. 3. Layout of the laboratory for experimental evaluation of RETaIL.

In a real store, instead of knowing the exactly position accurately within centimeters, the most important localization task is to obtain the real time information about which area is the query clothes locate at and whether the clothes were moved. To this end, firstly we divided room into four sub-quadrants (SQ), within which shelves are closely deployed. Numbers of tags in these sub-quadrants are 267, 90, 78 and 295, respectively. Secondly, we have the settings configured as “mobility” scan such that we get a high read rate, which makes it easier to see moving tags.

The readers collect tag IDs, frequency, phase and RSSI information for feature extraction. Models and parameters are trained offline before validation. For testing, we collect data from three different time periods in three days (10 min each time), within which about 2.6–3.1 million signals are received by five readers. These signals are sent to the system for localization and the prediction accuracies are shown in Table 1. From the table we can see that among the three algorithms, the highest accuracies are

Table 1. Prediction accuracies in laboratory

Accuracy	SVM	J48	Cloth group	Voting
Day 1	89.86%	88.62%	89.19%	93.74%
Day 2	93.39%	88.64%	88.78%	93.69%
Day 3	91.76%	88.86%	89.00%	93.18%
Average	91.67%	88.71%	88.99%	93.54%
Time	5.3 s	2.7 s	3.7 s	6.0 s

obtained by SVM. For three independent tests, the average accuracies for three algorithms are 91.67%, 88.71% and 88.99%, respectively. By combining all results to generate stable prediction location, accuracies of final result after voting process are 93.74%, 93.69% and 93.18%, increase consistently from highest accuracy that obtained from single algorithm. Moreover, it only takes 6 s to locate 730 clothes from ~3 million signal, indicating RETaIL can provide real-time localization on single cloth.

4.2 Experiment Results in Levis Store

One of the key innovations of RETaIL is performing localization in very clutter environment. The previous section gives an insight that RETaIL is capable of predicting locations for hundreds of clothes simultaneously. Here we further test the system in real retail store, a Levis outlet store in Napa Valley, which also adopts Intel Retail Sensor Platform for better control of inventory accuracy. Environment is more complicate in this test due to the crowded people and various collisions and reflections in the outlet store.

The layout of the store is shown in Fig. 4, in which each color represents one of the seven sub-quadrants that are taken care of by a shop assistants. White rectangles with four digits designate RFID readers that are dispersed in the room. The number of tagged clothes and readers are ~10 thousands and 25 respectively at our test period. All clothes are put on shelves, racks and tables densely while RDIF readers are deployed on ceiling.

The main purpose of item-level localization in store is to get real-time information about which sub-quadrant is the query clothes locate in and which assistant should be responsible for them if they are misplaced. As in real store they need to know item locations from time to time and readers need to keep collecting data all the time, the RFID settings used in store is slightly different from laboratory. Read rate is relative lower than in lab such that less storage space and less prediction time is needed.

Similarly, 10 min data is used for testing by comparing the predicted location with the manually collected ground truth data. The prediction process repeats three times on different testing data to ensure reliable results. About 0.89–0.94 million signals from ~600 clothes are extracted for feature extraction and prediction each time. Table 2 shows the prediction accuracies of three algorithms and final voting results. As expect, in a real outlet store with more complex environment, RETaIL still gives satisfying localization results with an overall accuracy of 90.79% and a 1.14% STD across test results for three days. For each day, different algorithms get best prediction performance. For Day 1, the highest accuracy of 90.02% is obtained by J48 while in

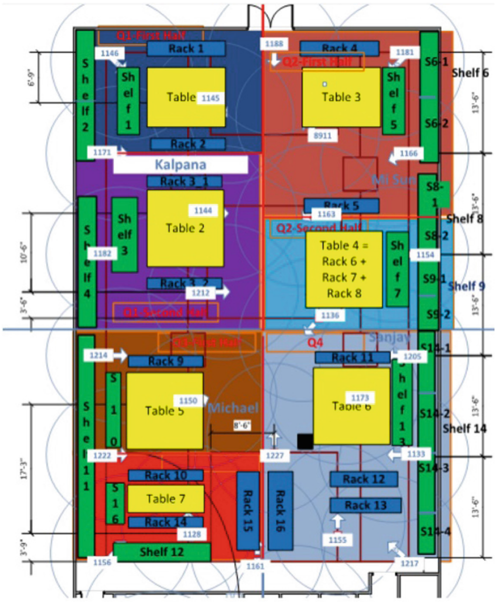

Fig. 4. Layout of Levis retail store in Napa valley.

Table 2. Prediction accuracies in Levis outlet store

Accuracy	SVM	J48	Cloth group	Voting
Day 1	90.02%	90.77%	84.64%	91.03%
Day 2	90.49%	89.60%	75.84%	89.55%
Day 3	91.79%	90.07%	80.75%	91.79%
Average	90.76%	90.15%	80.41%	90.79%
Time	1.3 s	1 s	1 s	1.6 s

Day 2 and Day 3, the highest accuracies of 90.49% and 91.79% are obtained by SVM. Overall, the average accuracies of voting result (90.79%) is better than that of using only SVM, J48 or cloth grouping, whose accuracy are 90.76%, 91.15% and 80.41%, respectively. Also, with lower read rate and less received signals, it takes only 1.6 s to perform localization for ~600 clothes, demonstrating the efficiency of our system.

It should be noticed that under such configuration, only part of tags are read in the evaluation process, making localization for unread clothes unavailable. Actually, with current configuration, a higher read rate is obtained as compared with deep scan mode and it's easier to get more signals from moved tags, making our system suitable for detecting misplaced clothes. For those tags that wasn't read by RFID reader, they may not be moved within 10 min. Localization for those clothes can be easily implemented by only extracting signal received from corresponding tags in a longer time range.

5 Conclusions

The proposed system guarantees a reliable indoor localization solution in retail environment. Different from previous methods in which only a small number of tags were taken into account, this work focuses on predicting locations for hundreds of tags accurately regardless of perplexing interference. RETaIL achieves robust localization results in complex environment by incorporating three machine learning algorithms that make use of both original and statistic features. By imitating store environment in a lab, RETaIL shows good localization performance. Further evaluation in Levis outlet store with thousands of clothes, 30 RFID readers, obstacles and crowded customers, demonstrates reliable localization accuracy of RETaIL. The accuracy and robustness make it suitable for item-level localization in various retail applications including store, supermarket, industry and warehouse.

References

1. Garfinkel, S., Rosenberg, B.: RFID: Applications, Security, and Privacy. Addison-Wesley, Boston (2005)
2. Zhang, Z., Lu, Z., Saakian, V., Qin, X., Chen, Q., Zheng, L.-R.: Item-level indoor localization with passive UHF RFID based on tag interaction analysis. IEEE Trans. Industr. Electron. **61**, 2122–2135 (2014)
3. Roussos, G.: Enabling RFID in retail. Computer **39**, 25–30 (2006)
4. Roussos, G., Kourouthanassis, P., Moussouri, T.: Appliance design for mobile commerce and retailteinment. Pers. Ubiquit. Comput. **7**, 203–209 (2003)
5. Yang, P., Wu, W.: Efficient particle filter localization algorithm in dense passive RFID tag environment. IEEE Trans. Industr. Electron. **61**, 5641–5651 (2014)
6. Chandrasekaran, V., Narayan, K., et al.: InPLaCE RFID: indoor path loss translation for object localization in cluttered environments. In: IEEE Tenth International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP 2015), pp. 1–6 (2015)
7. Ni, L.M., Liu, Y., Lau, Y.C., Patil, A.P.: LANDMARC: indoor location sensing using active RFID. Wirel. Netw. **10**, 701–710 (2004)
8. Madigan, D., Einahrawy, E., Martin, R.P., Ju, W.-H., Krishnan, P., Krishnakumar, A.: Bayesian indoor positioning systems. In: Proceedings of IEEE 24th Annual Joint Conference of the IEEE Computer and Communications Societies, pp. 1217–1227 (2005)
9. Öktem, R., Aydin, E.: An RFID based indoor tracking method for navigating visually impaired people. Turk. J. Electr. Eng. Comput. Sci. **18**, 185–198 (2010)
10. Yan, D., Zhao, Z., Ng, W.: Leveraging read rates of passive RFID tags for real-time indoor location tracking. In: Proceedings of the 21st ACM International Conference on Information and Knowledge Management, pp. 375–384 (2012)
11. Meguerditchian, C., Safa, H., El-Hajj, W.: New reader anti-collision algorithm for dense RFID environments. In: 18th IEEE International Conference on Electronics, Circuits and Systems (ICECS 2011), pp. 85–88 (2011)
12. Vorst, P., Schneegans, S., Yang, B., Zell, A.: Self-localization with RFID snapshots in densely tagged environments. In: 2008 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 1353–1358 (2008)

13. Joshi, G.P., Mamun, K.M.A., Kim, S.W.: A reader anti-collision MAC protocol for dense reader RFID system. In: WRI International Conference on CMC 2009, pp. 313–316 (2009)
14. Bueno-Delgado, M.V., Ferrero, R., Gandino, F., Pavon-Marino, P., Rebaudengo, M.: A geometric distribution reader anti-collision protocol for RFID dense reader environments. IEEE Trans. Autom. Sci. Eng. **10**, 296–306 (2013)
15. Eom, J.-B., Yim, S.-B., Lee, T.-J.: An efficient reader anti-collision algorithm in dense RFID networks with mobile RFID readers. IEEE Trans. Industr. Electron. **56**, 2326–2336 (2009)
16. Li, H., Ye, C., Sample, A.P.: IDSense: a human object interaction detection system based on passive UHF RFID. In: Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, pp. 2555–2564 (2015)
17. Li, H., et al.: PaperID: a technique for drawing functional battery-free wireless interfaces on paper. In: Proceedings of the 2016 CHI, pp. 5885–5896 (2016)
18. Neeraj, D.B., Girja, S., Ritu, D.B., Manisha, M.: Decision tree analysis on J48 algorithm for data mining. JARCSSE **3** (2013)
19. Chang, C.-C., Lin, C.-J.: LIBSVM: a library for support vector machines. ACM Trans. Intell. Syst. Technol. (TIST) **2**, 27 (2011)
20. Gao, Z., Ma, Y., Liu, K., Miao, X.: An indoor multi-tag cooperative localization algorithm based on NMDS for RFID. IEEE Sens. J. **17**(7), 2120–2128 (2017)