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Automatic detection of false positive RFID readings using machine learning algorithms

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A R T I C L E I N F O

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A B S T R A C T

Radio frequency identification (RFID) has been widely used for the automatic identification, tracking and tracing of goods throughout the supply chain from the manufacturer to the customer. However, one technological problem that impedes the productive and reliable use of RFID is the constraint of false positive readings, which refers to tags that are detected accidentally by the reader but not the ones of interest. This paper focuses on the use of machine learning algorithms to identify such RFID readings. A total of 11 statistical features are extracted from received signal strength (RSS) and phase rotations derived from the raw RFID data. Each of the features is highly statistically different to distinguish the false positive readings, but satisfactory classification cannot be achieved when these features are considered individually. Classifiers based on logistic regression (LR), support vector machine (SVM) and decision tree(DT) are constructed, which combine all of the extracted features to classify the RFID readings more effectively. The performance of the classifiers is evaluated in a real-world factory. Results show that SVM provides the highest accuracy of up to 95.3%. DT shows slightly better accuracy (92.85%) than LR (92.75%), while LR has the larger area under the curve(0.976) than DT(0.949). Overall, machine learning algorithms could achieve accuracy of 93% on average. The proposed methodology provides a much more reliable RFID application as false-positive readings are detected immediately without human intervention, which enables a significant potential of fully automatic identification and tracking of goods throughout the supply chain.

1. Introduction

Radio frequency identification (RFID) can be used to enhance visibility and traceability of supply chain. Once the product is attached with the RFID tag from the beginning of the supply chain, it is assigned a unique electronic product code (EPC) and then can be automatically identified, tracked and traced from the supplier to the customer. Shipping from distribution centers to retailers is one of the key processes in the supply chain. In order to ensure the smooth flow of goods, RFID has been commonly deployed in the warehouse and distribution centers (Keller et al. 2012). The goods attached with tags are automatically registered by the RFID reader when loaded to a truck after passing through the portal.

However, one technological constraint hinders the effectiveness of the RFID application in the warehouse. RFID reader can detect any object attached with the tag that appears in the reading range of the radio frequency field (Ju Tu and Piramuthu 2008). But the reader cannot distinguish between tagged tags that actually pass through the portal and the ones that appear in the reading field by chance, it is highly likely that incorrect invoices will be issued and the retailer stores will pay for goods that they nether received nor purchased. A false positive RFID read corresponds to the tag that is detected by the RFID portal but not loaded to the truck. Therefore, the reliable and productive RFID application in the distribution center process remains doubtful without solving the false positive RFID readings(Bong et al. 2014). Various reasons contribute to the false positive problem. Physical conditions in the warehouse is complex. Metallic object and the truck itself may cause

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multipath reflections of RF signals, which can extend the read range of the reader(Keller et al. 2015). As a result, the tag assumed to be away from the reader can be unintentionally read. Other reasons include that a warehouse man might buffer a tag temporarily near the portal or he is passing by the portal with another tag when the RFID portal is reading(Keller et al. 2010).

Many efforts have been devoted to resolving the false positive problem. The available measures can be grouped into three categories, i.e. sliding-window, extra hardware, and RSS based method. Bai et al. (2006)proposed the sliding window method. The false positive readings with the occurrence rate below a noise threshold are filtered. This method considers the RFID data stream to be uniform flow, which is the ideal situation in practice. Jeffery et al. (2006)introduced the adaptive sliding window, SMURF, to compensate for the inherent unreliability of RFID data streams. A variant of sliding window mechanism was proposed by Bian et al. (2013)to eliminate the false readings in a RFID tracking system. The algorithm has demonstrated its superior performance than the traditional mechanism. Tu and Piramuthu (2011) proposed using extra readers to determine the false positive reading. When the tag is read by the two readers at the same time, it is considered to be actually present. Otherwise, the false positive readings are confirmed if the tag is read by none of the readers. Krigslund et al. (2012)presented a novel method focusing on a two-device setup, a reader and an interference source. The setup can impose intentional interference between the reader and tag. Experimental results showed that the false positive read was reduced by imposing interference.

The methods relying on extra hardware to identify false positive RFID readings can incur additional cost. Sliding window methods mainly utilize timestamps and tags readings to detect false positive readings. But there is more valuable information generated by the reader such as Received signal strength (RSS) and phase shift. RSS has been commonly used for indoor real time location system(Ni et al. 2004; Luo et al. 2011; Stella et al. 2014) and movement detection(Yao et al. 2015). The changes of object's orientation and location affect the RSS reflected by the RFID tag. These signal changes can be leveraged to detect the fluctuations caused by the tag motion. Parlak and Marsic (2013)extracted features from RSS and classified them as moving or still using statistical methods. A trauma resuscitation case study was used to evaluate their methods. Results showed that the accuracy achieved 80% in complex scenarios. Keller et al. (2010)proposed an algorithm that used the information gain criterion to separate tags that were loaded onto trucks and tags that were in range of the reader by accident. The algorithm was verified under real distribution center and results showed that RSS value was the most suitable tag characteristics than timestamps and antenna attributes. Keller et al. (2015)presented an empirical study using data mining techniques to detect false positive RFID tags based on the attributes derived from low level reader data. Moreover, they demonstrated that utilizing full spectrum of data reported by the reader hardware resulted in better performance than single-attribute classifier.

Machine learning has created new intelligent tool for automated extraction of useful information and knowledge from manufacturing systems and processes(K. Wang 2007). RFID and artificial intelligence have been implemented together to enhance the responsiveness of the logistics workflow(Lee et al. 2011). Zhong et al. (2014)introduced decision tree and SVM to excavate practical standard operation times (SOTs) from RFID-enabled real-time shopfloor production data. Supervised pattern classification techniques, including k nearest neighbor and SVM, were used to differentiate the individual tag(Bertoncini et al. 2012). Chernbumroong et al. (2013)presented an assisted living system that combines neural network and SVM to activities of an elderly person.

Phase value has attracted more attention in indoor localization(Hekimian-Williams et al. 2010; Zhou and Griffin 2012). But it is rarely used for the classification of RFID readings. This paper proposes a method that extract features from RSS and phase values reported by the RFID reader to determine the false positive readings using machine learning algorithms. The rest of this paper is organized as follows. Section 2 introduces the real-world factory where the RFID data are collected and our method is evaluated. Section 3 gives the technical background of RF signal propagation. Extracted features from RFID data are presented in section 4. LR, DT, and SVM classifiers are constructed in section 5. In Section 6 we describe the experimental results of the experiments, and discuss some of our findings. Finally, the conclusion and future research are given section 7.

2. Empirical evaluation

An RFID enabled smart factory is set up by shanghai polytechnic university (SPU) in cooperation with knowledge discovery laboratory (KDL) in Norwegian University of Science and Technology (NTNU).

2.1. Experimental setup

Fig. 1 illustrates the process of the customized keychain from assembly to delivery. The keychain is assembled and produced in the smart factory to embody the typical characteristic of industry 4.0, i.e. mass personalization production. Each user is provided with the options to select the color of the keychain and print their names on it. All this information is transferred to the serial robot, which selects the raw materials, a bottom, a cover and a RFID tag, from the shelf and put them on the workbench equipped with a parallel robot, as shown in Fig. 1. Next the bottom, the cover, and the tag are assembled by the parallel robot. The finished keychain will then be put on the conveyor belt which can transfer the keychain to the printer workstation. The RFID tag will tell the printer what should be printed on the keychain. Finally, a mobile robot can deliver the keychain to the warehouse. All the processes above can be tracked and displayed in a RFID system, which is developed by APX systems in Norway. At each workstation, the assembly and the printer, the RFID reader antenna can read the tag. From the moment the tag is attached to the keychain, the product can be identified and tracked using RFID.

The functions of the RFID system are as follows. When the keychain is detected by the reader antenna installed at the assembly workstation, the RFID information will be displayed on the assembly list box. When the keychain arrives at the printer workstation, the printer list box will show the corresponding RFID information and the information in the

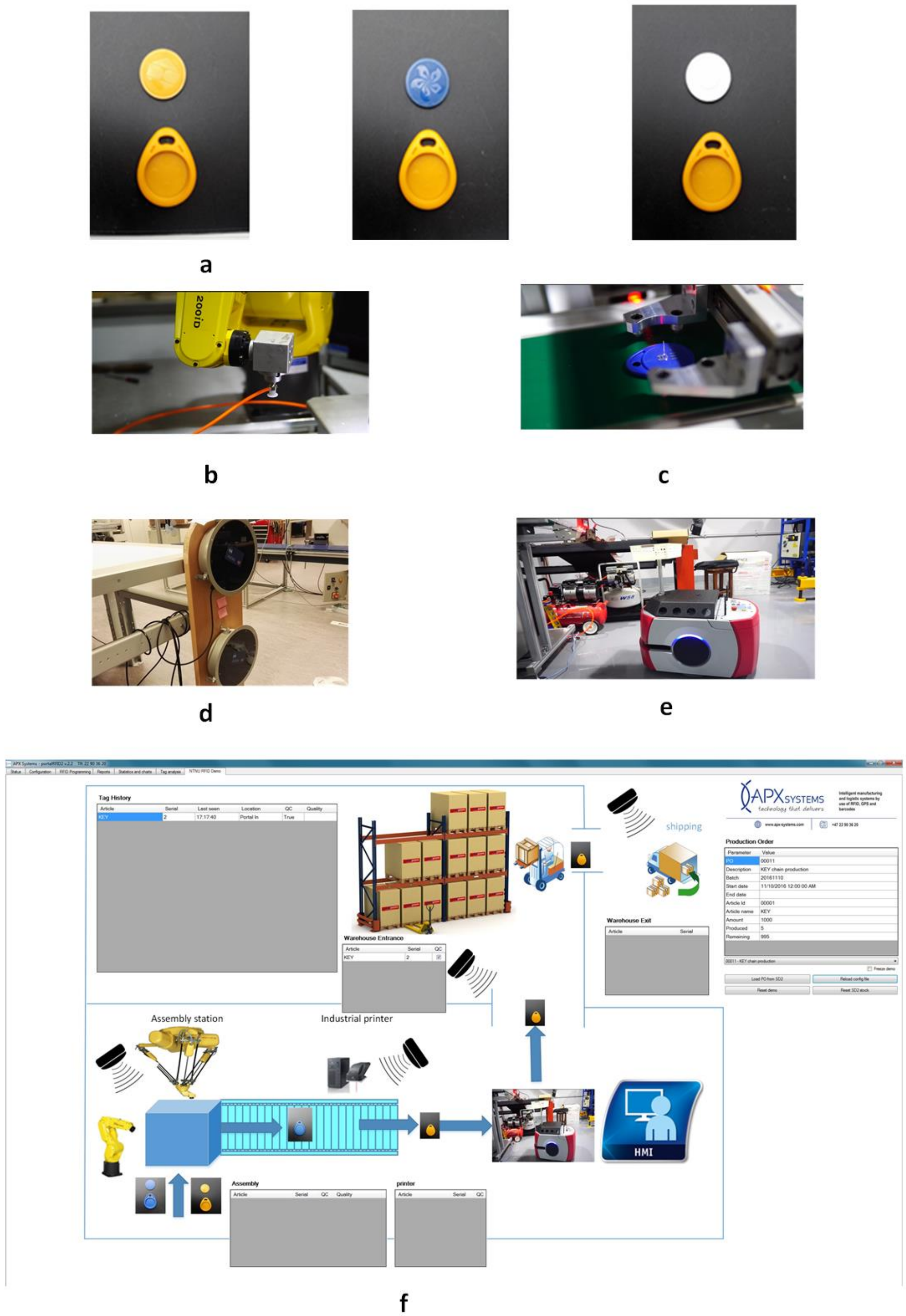

Fig. 1. The illustration of keychain customization (a) raw materials of key chain (b) serial robot (c) laser engraving workstation (d) portal (e) mobile robot (f) RFID system

assembly list box is cleared. This is real time tracking of RFID tags and all the RFID information during the production is displayed in the history list box and stored in the database of the RFID system for further research.

2.2. Data collection

Two reader antennas (Impinj Brickyard) are mounted on the portal. They are connected to Infinity 610 UHF reader which can report RSS, phase, timestamp and EPC. We recorded 2000 keychains tagged with RFID during our experiment, where 1000 of them were moved tags passing through the portal. Others were static tags that just appeared in the read range of the RFID portal by accident, i.e. the false positive readings. The period during which the RFID data are collected lasts 5 seconds, which is called the data gathering session. At each data gathering session, the tag is approximately interrogated by the RFID portal for 709 times. After the data collection is completed, we will extract features from the readings and classify them as moved tags or static tags using different machine learning methods.

3. RFID signal propagation theory

The brief introduction of the technical background on radio frequency signals and their propagation model are given in this section. Passive RFID system leverages backscatter radio link to communicate. Fig. 2 provides the conceptual diagram of the backscatter communication between a tag and a reader. Passive tags have no battery. Instead, they draw power from the reader, which transmits electromagnetic waves that induce a current in the tag's antenna. The RF signal transmitted by the reader is reflected off the tag, received back at the reader and processed to decode the data. The tag will reply the reader's query by changing the impedance on its antenna and modulates its data on the backscatter signals using ON_OFF keying(J. Wang and Katabi 2013).

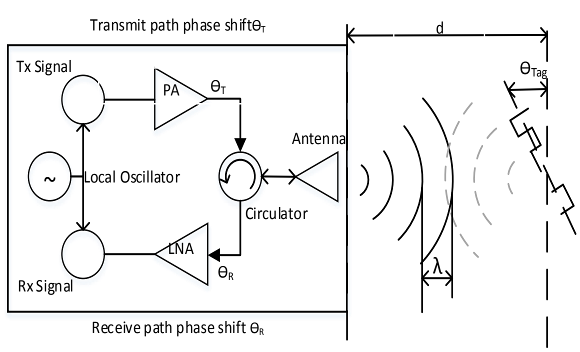

Fig. 2. Radio wave propagation between reader and tag

3.1. Received signal strength

RSS is the most common measurement for the distance between reader and tag. In free space propagation, RSS is positively correlated with the distance between a transmitter and a receiver. The distance can be expressed by the extensively used log-distance path loss model(LDPL) as follows (Hossain et al. 2013):

$$PL(d) = 10\log\left(\frac{TG_rG_t\lambda^2}{16\pi^2}\right) - 10\alpha\log d + X_\sigma \qquad (1)$$

Where d is the distance from the tag to the reader, $PL(d)$ is the free space path loss from distance d, G_r and G_t are the antenna gains of the reader and the tag, respectively, λ is the wavelength, α is the path loss exponent, and X_σ is a random variable that follows a Gaussian distribution, $X_\sigma \sim N(0,\sigma)$. X_σ is used to model the fluctuation of RSS due to multipath reflection, obstruction and variation of tag orientation (Bekkali et al. 2007).

3.2. Radio frequency phase shift

Most COTS RFID readers support the report of phase shift θ, which is a phase difference between the transmitted wave and the backscattered wave. When the wave travels from the reader antenna to the tag antenna, a phase shift is generated, which is related with the distance d. As illustrated in Fig.1, d is the distance from tag to reader. The total propagation distance of RF signal from the reader to the tag and back again is $2d$. The measured phase is a function of the wavelength λ and total propagation distance $2d$. The formula can be expressed as:

$$\theta = \left(\frac{2\pi}{\lambda} \times 2d + \theta_T + \theta_R + \theta_{Tag}\right) \bmod 2\pi \qquad (2)$$

where θ_T, θ_R, and θ_{Tag} are the additional phase rotations introduced by the reader transmitter, receiver and tag respectively. As phase shift has an inherent ambiguity of 2π radians, an unknown number of wavelengths are also included in the distance from tag to reader(Huiting et al. 2013).

4. Feature extraction

As stated in the section above, RSS and phase values are closely related with the distance between the tag and reader. Therefore, the changes of object's orientation and location will affect the RSS and phase values of the signal reflected by the RFID tag. These signal changes can be leveraged to detect the fluctuations caused by the tag motion. A total of 11 statistical features, listed in Table 1, are extracted from RSS and phase values to characterize the different RFID readings. The reasons for the selection of these 11 features are elaborated at the following.

Fig. 3 displays the RSS and phase readings during a data gathering session. As can be seen from Fig. 3(a), the max RSS for a moved tag is larger than that of a static tag. When the tag is passing through the portal, the moved tag is expected closer to the reader antenna. According to Eq. (1), the moved tags tend to have a higher RSS value. Meanwhile, the distance between the tag and the antenna changes continuously when the tag passes through the portal and the RSS for the moved tag will change correspondingly. Fig .3(a) reveals that the RSS values increase first, reaching the maximum at around 3 seconds, then decrease again, which indicates that the tag moves toward the portal, passes through it and then moves away from it. On the contrary, the RSS values for static tags are relatively constant. The variance of the moved tags is significantly higher than that of the static tags. Besides, Fig.3 (a) shows that the moved tag is interrogated more often than the static tag. These observations indicate that max RSS, average, variance, range of RSS, and number of RSS readings are statistically different features between the moved tags and static tags.

Fig. 3(b) shows the phase readings for the moved tag and static tag. The phase values display a similar distribution with that of RSS. Since the distance between the moved tag and the antenna changes continuously, the phase values will change as well. As a result, the variance and range of phase values for the moved tag are larger than that of the static tag based on Eq. (2). Therefore, variance and range are extracted from the phase values to differentiate the moved tags from the static tags. Another interesting finding about phase values is that they are periodic and repeat every 2π radians, as shown in Fig. 3(b). It is difficult to determine whether the tags are moving away from the portal using only phase readings. But at least one thing can be confirmed from Fig.3(b) that one tag is moving while the other is static.

In addition, statistical features extracted from the histograms of RSS and phase distributions are also utilized to characterize the RFID readings. Both kurtosis and skewness describe the shape of the histograms. Skewness is a measure of asymmetry of data distribution around the mean value. While kurtosis is a measure of whether the data are heavy-tailed or light-tailed. These parameters can be calculated as,

$$kurtosis = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\overline{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i-\overline{x})^2\right)^2} \tag{3}$$

$$skewness = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\overline{x})^3}{\left(\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i-\overline{x})^2}\right)^3} \tag{4}$$

Where $\overline{x}$ is the average value of the data points, n is the number of data points x_i .

Fig. 3(c) and Fig.3(d) display the histograms of RSS for static tag and moved tag respectively. Compared to the moved tag, the static tag tends to have symmetrical distribution because of its relatively stable position. Therefore, the skewness of static tags is close to zero. It is also observed that the moved tag tends to have a heavy-tailed distribution. The kurtosis of the moved tag is larger than that of the static tag. The histograms of phase values for the static tag and the moved tag are given in Fig.3(e) and Fig.3(f). The phase distribution displays the similar statistical characteristics to RSS distribution. Hence, both the skewness and kurtosis of RSS and phase values are extracted to separate the tags.

Table 1

Extracted features from RSS and Phase shift

Features	Description	
Max RSS	F1	The maximum of the received signal strength during a gathering session. When the moved tags move through the portal, they tend to have a larger RSS because the distance to the antenna is closer than the static tags.
Mean RSS	F2	The average of the received signal strength during a gathering session. When the tags move through the portal, they tend to have a larger mean RSS because the distance to the antenna is closer than the static tags during most of the gathering session.
RSS variance	F3	Because the distance of the moved tags to the antenna changes continuously when the moved tags pass through the portal, they tend to have a larger variance.
RSS range	F4	The difference between maximum received signal strength and minimum Received signal strength collected during a gathering session.
RSS Skewness	F5	Represents asymmetry of the RSS's histogram with respect to its mean value. Static tags tend to have a symmetrical RSS distribution.
RSS Kurtosis	F6	Measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution. Moved tags tend to have a heavy-tailed RSS distribution.
Phase variance	F7	Because the distance of the moved tags to the antenna changes continuously, they tend to have a larger variance.
Phase range	F8	The difference between the maximum and minimum measured phase values during a gathering session
Phase Skewness	F9	Asymmetry of the phase's histogram with respect to its mean value. Static tags tend to have a symmetrical phase distribution.
Phase Kurtosis	F10	Measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution. Moved tags tend to have a heavy-tailed phase distribution.
Count	F11	The total number of interrogation times during a gathering session. Moved tags tend to have a higher number of reads because they pass through the portal and are closer to the antenna.

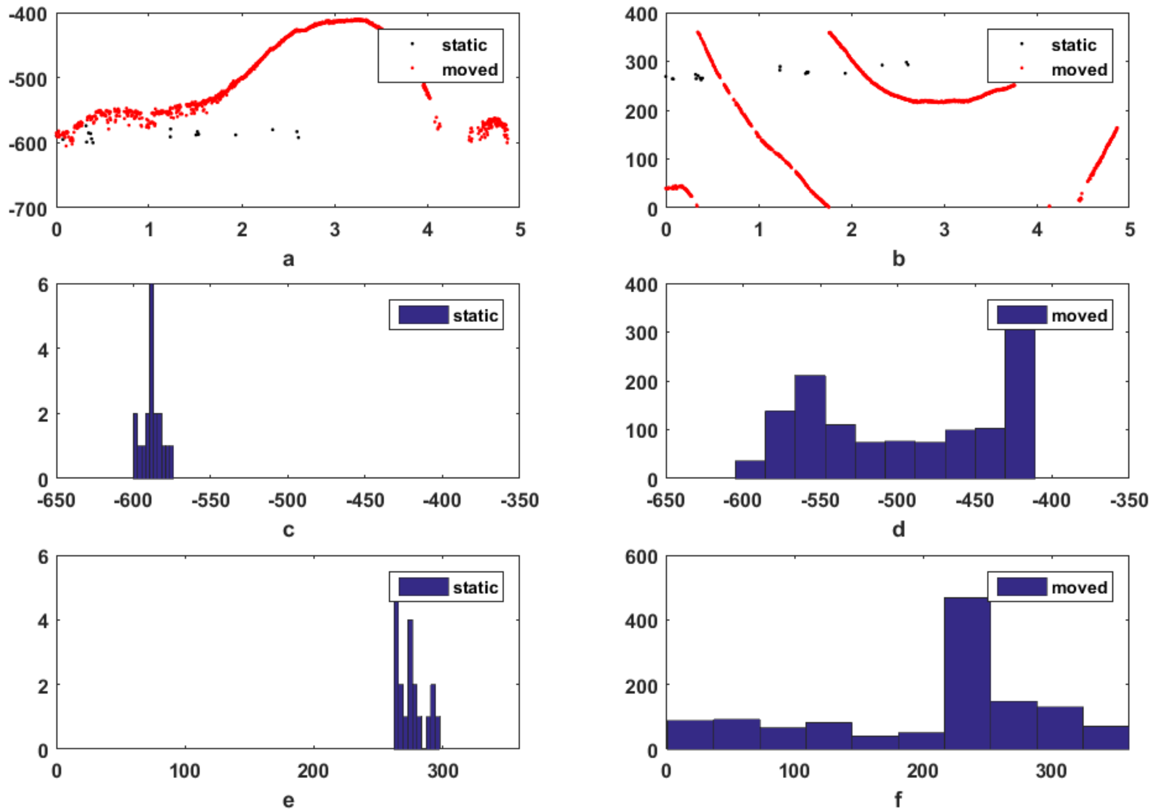

Fig. 3. Illustration of RFID reads for moved and static tags (a) RSS distribution (b) Phase distribution (c) RSS histogram (d) RSS histogram (e) Phase histogram (f) Phase histogram

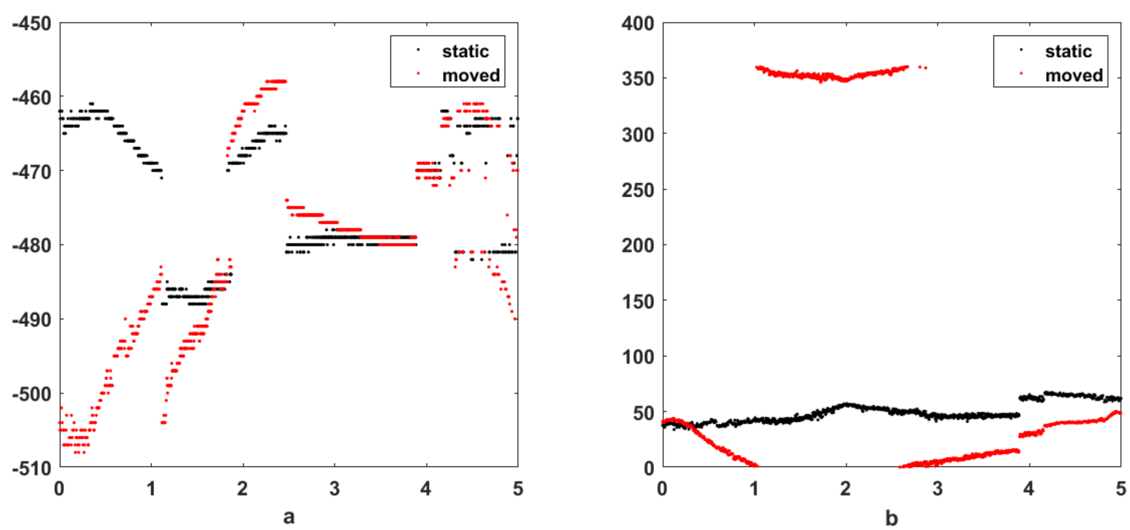

Fig .4. Comparison between RSS and phase values (a) RSS distribution (b) Phase distribution

According to Eq. (1), RSS is largely influenced by the environment, such as the multipath reflections of signals and obstruction. Thus, there may be discrepancy between the measured RSS values and the distance from the RFID antenna to the tag. Sometimes, even though the tag is far away from the antenna, its RSS values are still very high which may result in classification error. Based on the measurement of RSS values, it is difficult to differentiate the moved tag from the static tag

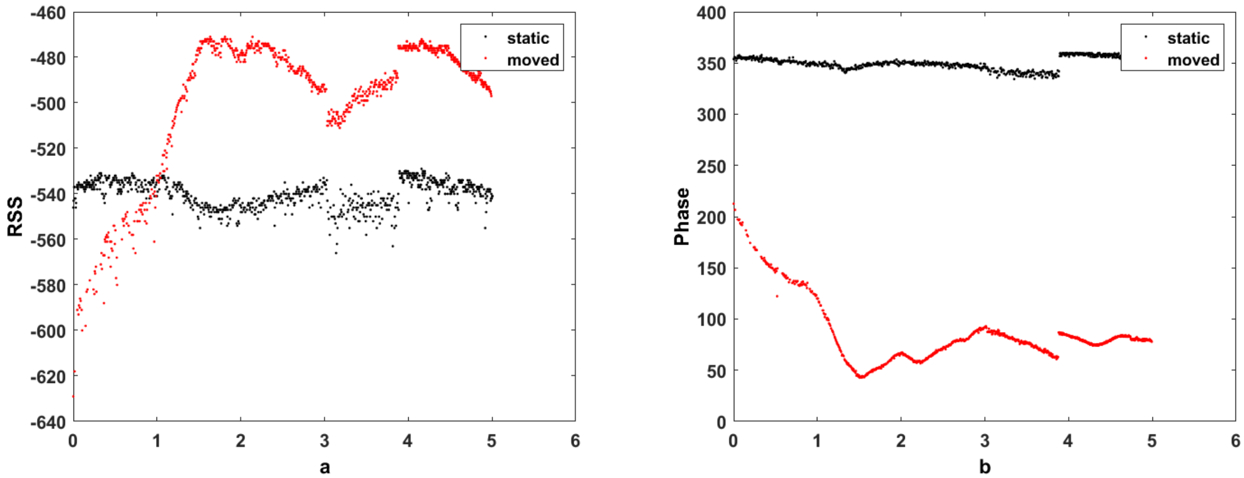

Fig .5. Characteristics of phase values (a) RSS distribution (b) Phase distribution

by only visualizing the RSS distribution, as shown in Fig. 4(a). The RSS values of the moved tag are mingled with that of the static tag. By contrast, phase values are more accurate than RSS and less affected by the environment, which can be verified by Eq. (2). The phase value is closely related to the hardware characteristics and the distance between the antenna and tag. Given that attribute, phase shift can supplement RSS to make better discrimination. As shown in Fig .4(b), the moved tag and the static tag are clearly separated.

As phase shift has an inherent ambiguity of 2π radians, the distance between the tag and reader antenna cannot be reflected from the phase shift directly. Hence, it is meaningless to differentiate the tags by comparing the max phase value and mean phase value, which can be illustrated in Fig. 5. The RSS distributions of the moved tag and the static tag are shown in Fig. 5(a). We can tell them apart intuitively through the RSS distribution, because the max RSS of the moved tag is larger than that of the static tag. But Fig. 5(b) shows the contrary result, where the max phase value of the static tag is larger than that of the moved tag, despite the moved tag is closer to the portal antenna than the static tag. Therefore, the max and mean phase values of the tags are excluded from the extracted features.

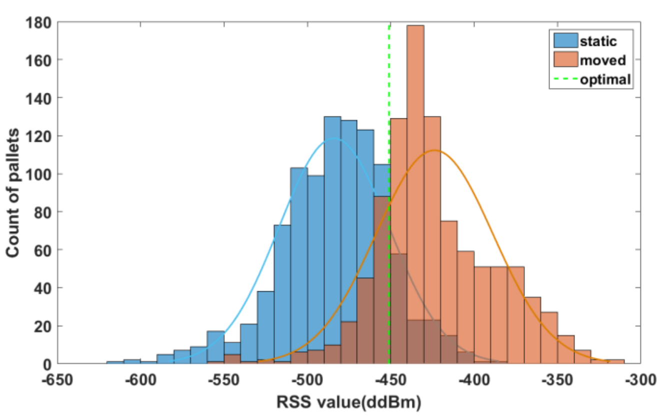

Fig. 6. Tags identification using maximum RSS

Even though all the 11 statistically different features listed in Table 1 contribute to differentiating the tags, satisfactory classification cannot be achieved when the features are considered individually. For example, the optimal threshold of max RSS for tags differentiation is at -451ddBm. The result is illustrated in Fig. 6. This parameter separates the tags with 85.49% specificity, 82.50% sensitivity, and 84.25% accuracy. This accuracy is not enough and the sensitivity is rather low which means quite a few moved tags are incorrectly identified as static tags. Fig. 7 depicts all of the individual feature's performance. The result indicates that although each feature result in statistically differences in identifying the moved tags and static tags, none of the separate feature enables the accuracy of above 90%. Consequently, it makes sense to combine the entire individual feature together using machine learning algorithms to distinguish the tags.

5. Classifier development

Data classification consists of two phases, including the training phase and classification phase. In the training phase, machine learning algorithms build a classifier based on the training set made up of data tuples and their corresponding class labels. The tuple is composed by an n -dimensional feature vector denoted by $X = (x_1, x_2, ...x_n)$. Because 11 features are extracted from the RFID readings, n equals 11 and the class labels are moved or static. Three commonly used machine learning algorithms are employed to construct the classification model: decision tree(DT), support vector machine(SVM), and logistic regression(LR).

Decision tree

Decision tree adopts a tree structure to predict a tuple. The tree structure is constructed from the root to a leaf node which holds a class label. Each non-leaf node represents a splitting criterion on a given feature and each brunch represents an

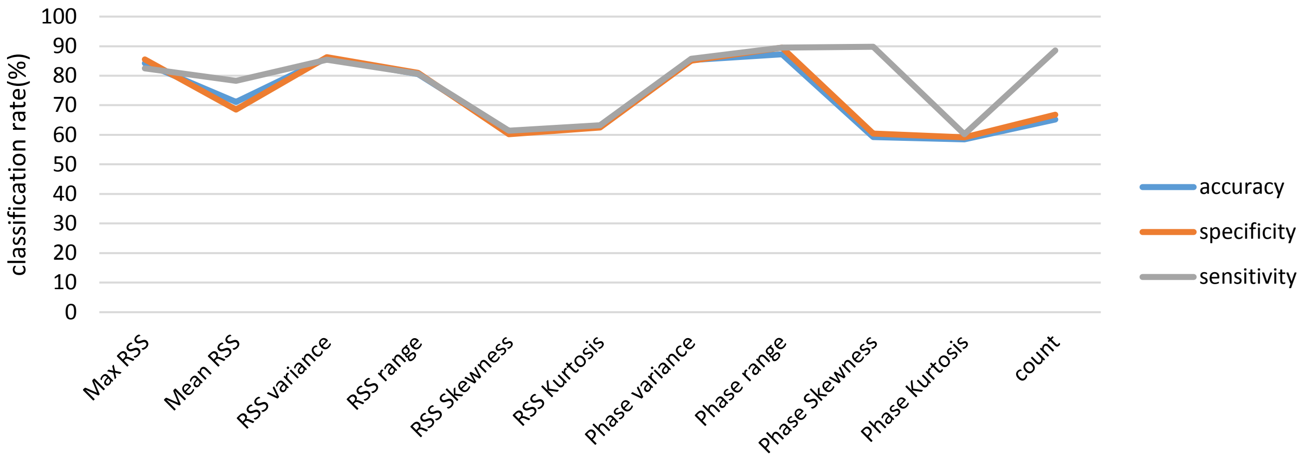

Fig. 7. Performance of individual feature

outcome of the split criterion. The splitting criterion is determined by the attribute selection measure. We build the decision tree classifier in Matlab, which uses the CART algorithm. The Gini index which measures the impurity of the data set is utilized in CART to find the splitting criterion.

Let D be the training set which contains m distinct class labels C_i .The Gini index is expressed as(Han et al. 2011),

$$Gini(D) = 1 - \sum_{i=1}^{m} p_i^2 \quad (5)$$

Where p_i denotes the probability that a tuple in D belongs to class C_i .

The Gini index produces a binary split for each attribute. Suppose A is a continuous-valued attribute with v distinct values v_i . In order to get the best binary split on A, each possible split-point are evaluated. If a binary split on A separates D into D_1 and D_2, where D_1 is the set of tuples that satisfy $A \leq$ split point, and D_2 is the set of tuples that satisfy $A \geq$ split point, the Gini index of D given that partition is

$$Gini_A(D) = \frac{|D_1|}{|D|} Gini(D_1) + \frac{|D_2|}{|D|} Gini(D_2) \quad (6)$$

The split point which gives the minimum Gini index for A is taken as the split-point.

Support vector machine

Support vector machine is a supervised machine learning method for data analysis and pattern recognition. SVM classifies data by nonlinearly mapping the original data to high dimensional feature spaces first, and then finds the linear optimal hyperplane, a decision boundary, to separate the data set of one class from another. The hyperplane with the maximum margin between the two classes is sought by SVM classifier. The hyperplane can be written as

$$\omega^T \cdot \varphi(X) + b = 0 \quad (7)$$

Where ω is the weight vector, $\varphi(\cdot)$ is the nonlinear mapping and b is the bias. The optimal hyperplane is defined by finding ω and b which minimize the following function(Schölkopf et al. 2000)

$$\min \ \frac{1}{2}\omega^T \cdot \omega + C\sum_{i=1}^{n} \xi_i \quad (8)$$

Subject to

$$y_i(\omega \cdot X + b) \geq 1 - \xi_i \text{ and } \xi_i \geq 0 \quad (9)$$

Where the slack variable $\xi_i = \max(0, 1 - y_i(\omega \cdot X + b))$ and C is the penalty parameter. The slash variable ξ_i is introduced into the Eq.(8) because the data is not always linearly separable. The penalty parameter C determines the tradeoff between increasing the margin and ensuring the data on the right side of the hyperplane. Radial basis function is selected as the kernel function, which is expressed as

$$G(x_i, x_j) = \exp\left(-\frac{\|X_i - X_j\|}{2\sigma^2}\right) \quad (10)$$

Where σ is the standard deviation.

Logistic regression

Logistic regression is a regression model which is used to predict the probability of categorical dependent variables. LR has been widely used in conditioning monitoring of cutting tool where the binary classified variables are normality and failure(Chen et al. 2011; Li et al. 2015). In our research, the categorical variables are moved and static tags. The relationship between the categorical dependent variables and the independent variables are measured by LR using the logistic function as follows,

$$g(z) = \frac{1}{1 + e^{-z}} \quad (11)$$

Given a feature vector $X = (x_1, x_2, \ldots x_n)$ of the RFID readings, the probability $h_\theta(X)$ of the categorical dependent variable y (moved=1, static=0) equals,

$$h_\theta(X) = g(\theta^T X) \quad (12)$$

Where θ is the regression coefficient which is determined by minimizing the cost function of logistic regression,

$$J = \sum_{i=1}^{m}\left[-y^i \log(h_\theta(X^i) - (1-y^i)\log(1-h_\theta(X^i))\right] \quad (13)$$

Where m denotes of the number of the tuples in the training set. The cost function is used to evaluate how well the LR model fits the training data.

6. Experimental results and discussion

The performance of the machine learning approaches to detect the false positive RFID readings is evaluated using 10-fold cross validation. The data set is randomly partitioned in ten subsets with one of ten subsets used as the test set while the others as the training set. A part of the data set is shown in Table 2. This process is repeated ten times until all ten subsets have been used for both training and testing. The average accuracy of the approaches in the ten rounds of cross validation is reported as metric for evaluation, which is defined as

$$accuracy = \frac{number\ of\ tags\ correctly\ classified}{number\ of\ tags} \quad (14)$$

Another two important measures used for evaluation are sensitivity and specificity, which are given as

$$sensitivity = \frac{number\ of\ tags\ correctly\ classified\ as\ moved}{number\ of\ moved\ tags} \quad (15)$$

$$specificity = \frac{number\ of\ tags\ correctly\ classified\ as\ static}{number\ of\ static\ tags} \quad (16)$$

The accuracies of the three machine learning approaches are shown in Fig. 8. SVM outperforms DT and LR with the highest accuracy of 95.5%±1.3 and the smallest standard deviation. This demonstrates that SVM has better data generalization and more reliability than the other two classifiers. DT shows

Table 2
Part of the data collection

No	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	Class
1	-449	-460.172	42.01631	36	-0.8158	4.310549	2053.988	359.8956	7.068851	52.68889	1222	0
2	-438	-446.138	16.4197	17	-0.206	1.935345	16.15839	19.77539	-0.12786	2.525491	972	0
3	-460	-476.578	89.70307	33	-0.33952	1.603428	50.45177	30.34424	0.752284	2.422366	1058	0
4	-362	-474.815	5159.725	196	0.357591	1.431107	15185.37	359.9176	-0.6555	1.654829	1957	1
5	-424	-468.277	1238.169	104	-0.31858	1.540273	1742.024	144.3329	0.240386	1.831543	956	1
6	-490	-514.898	135.6597	71	0.064726	3.966074	1390.072	359.9176	-8.39662	75.39645	765	0
7	-449	-507.212	199.5547	121	0.002688	7.27884	1540.425	348.371	1.107835	12.63264	226	0
8	-426	-465.986	1355.709	132	-0.73831	2.505734	7395.266	358.4509	-0.89449	3.17162	918	1
9	-408	-434.323	128.1182	45	0.707454	2.18809	49.32138	30.54199	0.373044	2.11012	854	0
10	-405	-448.63	954.8268	144	-0.64676	3.05545	3049.21	351.1725	-1.16882	6.496533	665	1
11	-447	-471.116	57.14106	42	0.559984	2.985954	468.2572	77.01965	-1.59286	3.756936	985	0
12	-557	-574.825	69.36718	44	-0.64326	3.383642	4.490083	11.10168	-0.25694	2.914503	114	0
13	-442	-455.827	35.05476	31	0.681721	3.115981	14485.9	311.6327	1.455441	3.123077	1100	0
14	-411	-494.363	3706.34	194	0.0036	1.459702	8352.52	358.6981	-0.64366	2.468081	1238	1
15	-385	-430.618	1510.693	170	-1.13711	3.717644	11185.91	319.455	0.672517	1.992163	872	1
16	-394	-453.314	2552.666	173	-0.76474	2.513102	7383.64	359.4012	0.082959	2.093898	796	1
17	-478	-489.757	37.76601	29	0.204112	2.333488	186.2932	45.93933	-0.27533	2.263785	915	0
18	-451	-473.034	30.23628	32	0.528525	3.262211	39.96239	22.94495	0.162246	1.63121	818	0
19	-479	-495.491	78.07341	32	0.051247	1.654391	10483.37	359.9615	2.199334	6.027944	1008	0
20	-462	-488.841	52.49726	41	1.29678	4.294829	46.91892	35.24963	0.67722	3.11346	684	0
21	-511	-543.959	973.7256	97	-0.64959	1.666619	111.8418	44.81323	0.35917	2.066272	122	1
22	-521	-555.523	388.3599	87	-0.19081	1.845874	2537.601	131.8744	0.539479	1.396659	1108	1
23	-429	-444.929	52.71275	38	0.239094	2.952003	133.0801	38.83667	0.475647	1.631656	926	1
24	-444	-461.766	94.40747	36	0.197591	1.938721	84.15629	31.84387	0.455939	1.949709	1280	0
26	-457	-487.138	397.8268	100	-1.32039	4.427495	983.5189	95.27893	0.220116	1.579562	727	1
27	-491	-504.203	112.7375	46	-0.93423	3.64336	656.345	93.86719	1.347638	3.469264	1009	0
28	-518	-526.565	34.79432	21	-0.62108	2.88111	21.67721	17.93518	0.309644	1.760684	315	0
29	-577	-584.667	50.33333	14	0.333067	1.5	9.271475	6.069946	0.169748	1.5	3	0
…	…	…	…	…	…	…	…	…	…	…	…	…
2000	-473	-484.459	56.17761	33	-0.57027	3.172882	68.97311	31.5033	0.888269	2.553791	988	0

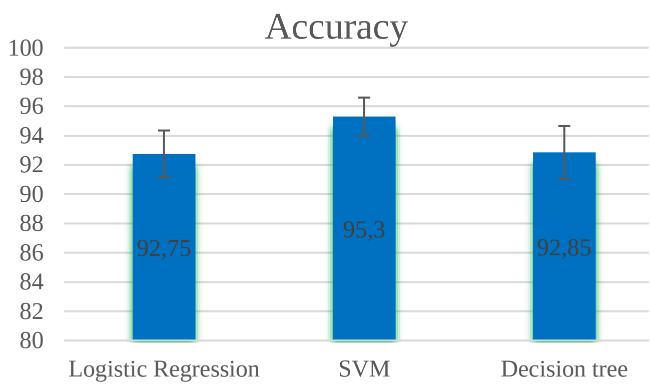

Fig. 8. Performance comparison among different machine learning algorithms

slightly higher accuracy (92.85%±1.8) compared to LR (92.75%±1.6). But LR has lower variance than DT during the ten rounds cross validation. The reason is that LR is intrinsically simple and is also robust to data noise. It is less prone to over-fitting.

Next, we compare their sensitivity and specificity. The results are shown in Table 3. Sensitivity quantifies the avoiding of false negatives while specificity quantifies the avoiding of false positives. False positive detection and false negative detection have different economic consequences. When a static tag is incorrectly identified as moved tag, it is called the false positive RFID read. The warehouse management system cannot distinguish it and assume the tags have been loaded to the truck. Consequently, incomplete consignments will be sent to the retail store, which may incur the risk of stock out in the worst case. By contrast, when a moved tag is incorrectly identified as a static tag, the warehouse management system will send excess shipments to the retail store, which may cause surplus of the inventory. From a practitioner's point of view, the false positive RFID readings can lead to more serious problem. Therefore, classification approaches with the higher specificity are preferred.

As shown in Table 3, all of the three classification methods show higher specificities than their sensitivities. The specificity of LR is 92.9% which is 0.3% higher than its sensitivity. DT performs slightly worse than LR with specificity 0.1% higher than its sensitivity. SVM yields best result in terms of sensitivity (93.9%) and specificity (96.7%). These results are also supported by their receiver operating characteristic (ROC) curves as shown in Fig. 9. The ROC curve is used to visualize

Table 3
Confusion matrix of different machine learning algorithms

Logistic regression		
True \ Predicted	Moved [%]	Static [%]
Moved	92.6	7.4
static	7.1	92.9
SVM		
True \ Predicted	Moved [%]	Static [%]
Moved	93.9	6.1
static	3.3	96.7
Decision tree		
True \ Predicted	Moved [%]	Static [%]
Moved	92.5	7.5
static	7.4	92.6

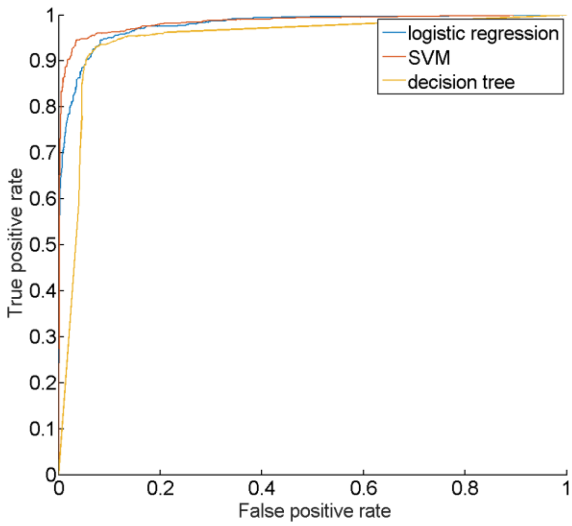

Fig. 9. ROC curves for LR, SVM and DT respectively

the performance of a binary classifier as the discrimination threshold varies. The area under the curve (AUC) measures how well the classifier distinguish the moved tags from the static tags. After ten rounds of cross validation, the ROC curves are obtained for the three machine learning algorithms. Their AUC values of LR, DT and SVM are 0.976, 0.949, and 0.985 respectively. SVM still has the best performance in terms of AUC. The results also indicate the AUC value of LR is larger than that of DT, even though the accuracy of DT is higher than LR. The explanation for that is the overall accuracy is computed at the discrimination threshold value of 0.5, while ROC is computed at all possible threshold values. Therefore, ROC curve gives the more comprehensive comparison. LR shows better discrimination ability than DT to correctly identify the tags in this case.

Note that the percentage of the static tag incorrectly identified as moved tag is lower than that of the moved tag incorrectly identified as static tag for all the three classifiers. The false positive percentage and the false negative rate of LR are 7.1% and 7.4% respectively. The false negative percentage of DT shows 0.1% higher than its false positive percentage. While, SVM almost reduces the false positive percentage by one half compared to LR and DT. This result reveals that the moved tag is more likely to be incorrectly classified than the static tag. The noisy features of moved tags contribute to this result. When the moved tags pass through the portal, their RSS values and phase shifts change continuously. The RFID readings of the moved tags tend to have more noise than the static tags which have a relatively constant RFID reading. As a result, the statistical features extracted from RSS and phase shift are expected to be noisy for moved tags.

The experimental results above indicate that all of the machine learning algorithms identify false positives with high accuracy. These results are also supported by their corresponding ROC curves. Moreover, Table 3 shows that all of the machine learning algorithms have higher specificities than sensitivities, which implies that they discriminate false positives more effectively. From the prospective of economic consequence, false positives may lead to the risk of stock out in the worst case. Therefore, the practitioner in supply chain can benefit from the proposed method.

7. Conclusion and future research

In this paper, a new method by extracting features from RSS and phase shifts of received RFID signal for automatic detection of false positive RFID readings is proposed. Machine learning algorithms are applied to distinguish the moved tags from the static tags which appear in the read range of the RFID reader by accident. Our method is evaluated in a smart factory built by SPU with cooperation of KDL in NTNU. The results demonstrate that our methods achieve an average accuracy of 93%.

Previous researches focus on the use of extra hardware and sliding-window approach. Nevertheless, additional hardware can incur unnecessary cost. The sliding-window approach mainly relies on the counts of RFID reads and the corresponding timestamps to detect the false positives. In contrast to these approaches, we instead extract much more features from RFID data and apply machine learning algorithms to distinguish the false positives. Compared to the previous approaches, our method is cost effective and leads to better performance.

The main limitation of our study is the volume of RFID data. In the future, more data samples will be collected so as to cover as many variants of RFID readings as possible. Since a large volume of data can provide greater insights than any simulated data or laboratory experiments, our method can be evaluated more comprehensively and thoroughly.

Now only statistical features are utilized to build the classification model. Further studies will also extract additional features from RFID signals using wave packet decomposition to strengthen the performance of our method. It is reasonable to take more features into account, which can yield a high degree of accuracy.

Currently, traditional machine learning models are constructed to identify the false positive RFID readings. With the increase of data samples and extracted features, more advanced and efficient supervised learning algorithms are probably able to achieve better classification accuracy.

Finally, even though the proposed method is used to detect the false positives at the shipment dock doors equipped with RFID system, there are much more fields of applications that need to solve the problem of false positive reads, such as RFID enabled self-checkouts and the monitoring of misplaced goods. Our proposed method can be transferred to these new areas to deal with the same problem.

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Highlights

- This paper presents a classification method for detection of false positive RFID readings.
- We collect RFID data from a joint factory built by NTNU and SPU.
- We extract received signal strength (RSS) and phase rotations derived from the raw RFID data.
- Experimental results demonstrate our proposed method achieves satisfactory accuracy.