Mobile RFID Tag Detection Influence Factors and Prediction of Tag Detectability

Minho Jo, *Member, IEEE*, Hee Yong Youn, *Senior Member, IEEE*, Si-Ho Cha, *Member, IEEE*, and Hyunseung Choo, *Member, IEEE*

***Abstract*—Radio-frequency identification (RFID) readers are powered RF devices that communicate with tags (whether mobile or fixed) and read necessary information to be processed. A mobile RFID tag is detected by an RFID antenna. In a mobile RFID where the RFID tag is attached to a mobile object such as a vehicle, a human, or an animal, information is more difficult to detect than in the case where the tag is attached to a stationary object. Currently, deployment engineers and researchers use trial-and-error approaches to decide on the best conditions of the tag detection influence factors which affect tag detectability (detection rate). As expected, these approaches are time consuming. Even though mobile RFID systems have become widely used in industry and tag detection problems are crucial at deployment, very few researches on them have been conducted so far. Thus, a quick and simple method for finding tag detectability is needed to improve the traditional time consuming trial-and-error method. In this paper, we propose a unique approach "the intelligent prediction method of tag detection rate using support vector machine (SVM)." The intelligent method predicts the mobile RFID tag detectability instead of the trial-and-error experimental procedures. The simulation results of the proposed method are very comparable to the trial-and-error experimental approach. The proposed intelligent method gives a very high accuracy of mobile RFID tag detectability prediction and proves to be superior to the current method in time as well cost savings. The predicted tag detectability results can be used for analyzing mobile RFID tag detection influence factors and their conditions.**

***Index Terms*—Intelligent mobile radio-frequency identification (RFID), prediction of tag detection rate (detectability), support vector machine (SVM), tag detection influence factors.**

I. Introduction

RADIO-FREQUENCY IDENTIFICATION (RFID) based on wireless radio communication is used for tagging and identifying stationary or mobile objects. With a special antenna device called RFID reader, RFID technology allows the objects to be labeled and tracked as they move from place to place. A typical RFID system consists of tags, readers, middleware, application program, and server [1]. The application program typically handles a specific task such as keeping track of the inventory in a warehouse, checking vehicles/human beings, or reordering the items removed from the shelf in a retail store based on the inventory data. It also takes an appropriate action according to the data extracted from the tag of the target item such as retail products, pallets, cartons, shipments, animals, human beings or vehicles. The middleware is a bridge interfacing the hardware components from the lower layer with the higher application program layer. In some literature, the application program and middleware together are called middleware. An RFID tag is a small RF chip coupled with a microprocessor, which can communicate with the RFID reader (sometimes called antenna). The RFID reader is a powered RF device communicating with the tags on the wireless side and one or more computers on the other side of wired infrastructure. There are two types of RFID: fixed RFID and mobile RFID. The fixed type RFID is for RFID reader to communicate with stationary tags. On the other hand, the mobile type RFID is either for mobile RFID reader to communicate with stationary tag, or for stationary RFID reader to communicate with mobile tag. In this paper, we explore the detectability (also know as detection rate or recognition rate) of mobile RFID tag (sometimes called tag in this paper).

In supply chain management and factory automation, for example, it is needed to track the vehicles (or conveyer) loaded with goods by attaching a tag to them. Information of the vehicle and goods such as vehicle number, contents of goods, and departure time and location data can be written into the tag, and then read out from it later at a specific point. Wireless radio communications between the mobile RFID tag and stationary RFID antenna are very sensitive to various factors such as the reader type, position and direction of the tag, material of object, angle of antenna, and moving speed of the mobile object [2]–[5]. Successful tag detection (also known as recognition) allows for RFID reader to receive a unique ID and other data from the detected tag which in turn are transmitted to the database server.

Recognizing the mobile tag by the reader means tracking successfully the mobile tag object which the tag is attached to. RFID tag detection is affected by the influence factors mentioned above.

The biggest hurdle that RFID systems need to overcome in practical use is the failure in reading the tags. The solution for this problem has been sought mostly with the empirical approach [6]–[8], while very few analytical approach has been done. The first formal literature on the empirical approach was

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published by Park *et al.* in 2006 [7]. They studied the tag detection rate empirically with conveyor speed and position of tag, antenna type, and read distance. The first research on the analytical approach was introduced by Jo *et al.* in 2007 [9]. They applied a backpropagation learning algorithm for the detectability prediction of tag on a water content. In 2008, detectability analysis and detectability prediction research of tag on a carton box on stationary pallet were accomplished [10]. Both previous researches were conducted for the case of fixed RFID or a very low moving speed tag that does not influence detectability and thus is ignored. Success of implementing RFID systems almost depends on the tag detectability at deployment. In mobile RFID, finding the best position, speed of mobile RFID tag, as well as the angle of RFID antenna (called "influence factor") is not easy but requires time consuming trial-and-error operations. Making a decision on the best influence factor condition is entirely based on tag detectability. This motivated us to introduce a time saving intelligent approach for the design of mobile RFID systems maximizing tag detectability in this paper.

In this paper, first the effect of factors on tag detectability is empirically analyzed through the traditional trial-and-error experimental method. We then propose a new approach for exploring the best influence factor conditions. The proposed approach is based on a machine learning method, support vector machine (SVM). The proposed method provides us with tag detectability by prediction instead of trial-and-error experiment. In the end, in order to prove the prediction accuracy of the proposed model, we compare the tag detection rate results by the current method and by the proposed method, respectively. The key idea of the proposed method is the prediction of the tag detection rate (detectability) without the trial-and-error operations. Thus, the ultimate objective of this paper is to propose a mobile RFID tag detectability prediction model using SVM which allows us to estimate the tag detection rate for exploring the influence factors without doing the very time consuming trial-and-error operations. Here, the proposed SVM model is trained using the accumulated data obtained by the trial-and-error experiment, and then the SVM model predicts the detectability of a mobile RFID tag. We summarize the major contributions of this paper as follows.

- Providing empirical analysis of detectability for mobile RFID.
- Proposing a SVM-based intelligent prediction method for tag detectability for mobile RFID as an alternative for the traditional trial-and-error method.
- Allowing for avoiding time consuming and high cost trial-and-error experimental method by using the predicted detection rate, when we explore the influence factor condition for mobile RFID.

The accuracy of tag detection rate prediction of the proposed method is verified by comparing the real experimental data and predicted data. The simulation is conducted. Extensive simulation results show that the prediction accuracy 96.15% is given for the speed change and 96.67% for the angle change. The proposed method is superior to the current trial-and-error method in terms of cost/time savings.

The rest of this paper is organized as follows. The background including the structure of RFID system and testbed environment used in this study are introduced in Section II. The proposed scheme is introduced in Section III. Section IV presents the performance evaluation of the proposed scheme using the data obtained by the current trial-and-error experimental approach. We conclude this paper with remarks on future work in Section V.

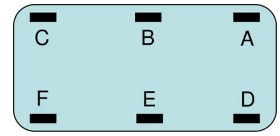

Fig. 1. Mobile RFID tag positions in the windshield of the vehicle.

II. BACKGROND FOR MOBILE RFID SYSTEMS

A. The Structure of RFID System

In a typical RFID system, passive tags are attached to an object such as goods, vehicles, humans, animals, and shipments, while a vertical/circular polarization antenna is connected to the RFID reader. The RFID reader and tag can radio-communicate with each other using a number of different frequencies, and currently most RFID systems use unlicensed spectrum. The common frequencies used are low frequency (125 KHz), high frequency (13.56 MHz), ultra high frequency (860–960 MHz), and microwave frequency (2.4 GHz). The typical RFID readers are able to read (or detect) the tags of only a single frequency but multimode readers are becoming cheaper and popular which are capable of reading the tags of different frequencies [11].

The RFID system used in the experiment in this paper is ThingMagic's Mercury 4 model and its detailed specifications are the following.

- Reader: 909–928 MHz with reading rate of 50 tags/s.
- RFID Antenna: 865–928 MHz of 6 dBi gain, circular polarization type.
- Air Interface Protocol: EPC Class1 Gen 2.
- RFID Tag: 915 MHz, EPC Class 1 Gen 2, Rafsec Short-Dipole product, 96 bit memory.
- Two double-combined UHF transmit/receive antenna sets are connected to an RFID reader.

The factors that influence detectability of the mobile RFID tag with fixed RFID reader include: (1) contents of the object; (2) type, position, and direction of tag; (3) moving speed of mobile tag; (4) angle of antenna; (5) power, type, gain, frequency range, and number of antennas; (6) work environment of the RFID system, etc. Here, the position of tag, speed of mobile tag, and angle of antenna are controllable factors, while the others are fixed with hardware and uncontrollable. Thus, in this paper, we consider the position of tag (x_3), moving speed of mobile tag (x_2), and angle of antenna (x_1) as influence factor.

B. The Testbed

In the trial-and-error experiment, tests are carried out manually to find the best influence factor conditions which allow for the mobile tag to be well detected by the RFID reader. Here 1-ton truck is used as the mobile object. A total of six RFID tags, A, B, C, D, E, and F are attached to the front window shield of the vehicle, as shown in Fig. 1. The size of the windshield is 140 cm $\times$ 80 cm and the height from the ground to the bottom of the windshield is 128 cm.

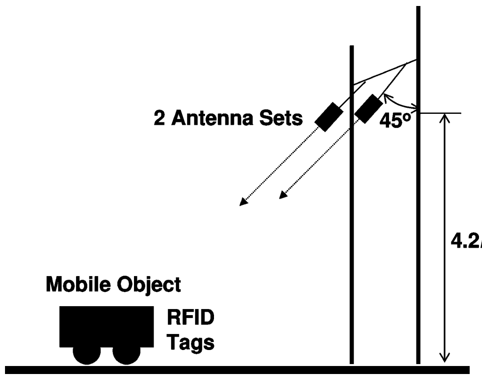

Fig. 2. Bar type testbed with two antennas.

The testbed is built on the outdoor road covered with asphalt. In order to obtain training datasets used for training the SVM-based tag detectability prediction model, we carry out the trial-and-error experiment by changing the speed of vehicle and angle of antenna of the bar type. With the bar type, two antenna sets are hung on the upright bars, as shown in Fig. 2. The height of the antennas is 4.2 m. The angle of the antennas can be adjusted in up and down direction.

The vehicle carrying the RFID tags in the front windshield passes through the antennas attached to the bar at different speeds. If any tag is correctly detected, the RFID reader reads the ID of the tag. As a result of detection rate (detectability), we can find out which one among the six positions, what antenna angle, and what speed allow higher detectabilty.

III. The Proposed Scheme

The problem here is how to find the best conditions of the influence factor allowing the highest detectability of the mobile tag. The proposed SVM model aims at predicting how much the mobile RFID tag can be detected with different influence factor conditions. The intelligent SVM-based tag detectability prediction model learns an unknown classifier based on the patterns of the training datasets, i.e., a set of input–output pairs. The well-trained classifier can classify an input pattern, and then it can predict an answer, the output based on the classified groups. In our problem, the output is whether the RFID tag is detected or not. The inputs are the influence factors such as angle of antenna, moving speed, and position of the tag. As a result, we can see how well the moving RFID tag can be detected with the given influence factor conditions.

Before we apply the SVM prediction model which is a nonlinear classification approach, we first check if the problem can be solved by the linear classification model.

A. Linear Model

First, the multiple-linear regression is applied to check if the prediction of detectability of RFID tag shows linearity. The general multiple-linear regression formulation of fitting a model is

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon \tag{1}$$

where β_0 is constant, β_i's are unknown parameters of regression coefficients, x_i is regressor variable, and ε is random error component such that $E[\varepsilon] = 0$, $V[\varepsilon] = \sigma^2$, and they are uncorrelated. The model describes a hyperplane in the k-dimensional space of the regressor variables [12]. A multiple-linear regression model for our problem representing the RFID tag detection is proposed as follows:

$$z = \beta_0 + \sum_{i=1}^{3} \beta_i x_i + \varepsilon \tag{2}$$

where β_0 is a constant, x_1 is the moving speed of the tag, x_2 is the angle of antenna, x_3 is tag position, ε is random error, respectively, and z represents whether the tag is detected or not. We checked how much the model is linearly fitted to the tag detectability using SPSS [13], a statistical and data management software package. The statistical results show that the linear model is not appropriate to predict the RFID tag detectability with relatively low R square value of 0.567 and with a standard error of 0.319. The R square represents the percent of the variability in the data accounted for by the linear model. Thus we need to apply nonlinear classification approaches such as back-propagation neural networks or SVM for the prediction of the RFID tag detection rate (detectability).

B. Support Vector Machine (SVM) Model

The SVM technique has been successfully applied to a wide range of nonlinear classification and regression problem. SVM was originally derived from the statistical learning theory [14], and has been well applied to the real-world field lately. It has been used for novelty detection and others [15]. The neural networks have been successfully applied for classification and regression problems. However, it has been generally accepted that the SVM technique outperforms the method for classification problems [16]–[19]. Compared to neural networks, the SVM model allows training a model with smaller amount of training datasets and high dimensional data, while giving global optimality. It is also easy to generalize the error.

1) Separable Case: We start with a simple case where the training datasets are linearly separable. The main idea with the SVM is to find an optimal classifier or an N-dimensional hyperplane that maximizes the margin between two classes, while minimizing the upper bound of error, as shown in Fig. 3.

There is no need to minimize the error in the linear classification case because all the examples can be completely separated by a linear separator. With two classes, let $x \in \Re^n$, $y \in \{-1, 1\}$ be the training instances, input and target, respectively. We also introduce $w \in \Re^n$ and $b \in \Re$ which are weight vectors and bias, respectively. The separating hyperplane can be expressed in w and b terms

$$\langle w, x \rangle + b = 0 \quad w_1 x_1 + w_2 x_2 + \cdots + w_n x_n + b = 0 \tag{3}$$

where w is normal to the hyperplane. The decision function of (3) for the optimal hyperplane is

$$f(x) = sign\langle w, x \rangle + b = 0. \tag{4}$$

Let us label the training dataset $\{x_i, y_i\}$ $i = 1, 2, \ldots, l, x_i \in \Re^n$, $y_i \in \{1, -1\}$. As shown in Fig. 3, $|b|/||w||$ is the length of the perpendicular line from the hyperplane to the origin. $||w||$

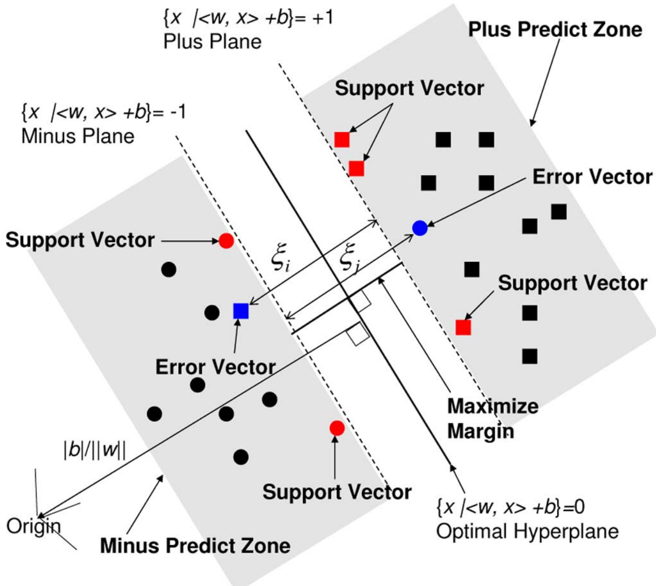

Fig. 3. Support vectors and optimal classification hyperplane for the case of two classes.

is the Euclidean norm of w. In particular, the margin between the plus plane and minus plane is $2/||w||$. The data points lying on the plus plane and minus plane closest to the hyperplane, are called support vectors. The plus plane and minus plane are parallel, i.e., they have the same normal and no training data points fall between them. For the linearly separable case, the SVM algorithm simply finds a separating hyperplane of the maximum margin, i.e., maximizing $2/||w||$. This can be performed by minimizing $||w||^2$ with all training data satisfying the objective function (5) and the constraints (6) and (7)

$$\text{Min } \frac{||w||^2}{2} \tag{5}$$

subject to

$$x_i \cdot w + b \geq +1, \text{ for } y_i = +1 \tag{6}$$
$$x_i \cdot w + b \geq -1, \text{ for } y_i = -1. \tag{7}$$

Equations (5) and (6) can be formulated into one set of inequalities

$$y_i(x_i \cdot w + b) - 1 \geq 0, \text{ for } \forall_i. \tag{8}$$

2) Nonseparable Case: As shown in Fig. 3, ξ_i, ξ_j lying across the plus or minus plane generate errors because the linear hyperplane cannot classify them. We can slightly modify the optimization problem to add a penalty called the slack variable ξ_i for violating the classification constraints

$$\text{Min } \frac{||w||^2}{2} + C\sum_{i=1}^{l}\xi_i \tag{9}$$

subject to the relaxed classification constraints

$$y_i(x_i \cdot w + b) - 1 + \xi_i \geq 0 \text{ and } \xi_i \geq 0. \tag{10}$$

ξ_i is the distance of error vectors to their correct places and $\sum_{i=1}^{l}\xi_i$ is a parameter which controls the tradeoff between the margin and error. The dual Lagrange multiplier optimization problem of the primary optimization problem, (9) and (10) can be formulated as follows:

$$\text{Max } L_D(\alpha) = \sum_{i=1}^{l}\alpha_i + \frac{1}{2}\sum_{i=1,j=1}^{l}\alpha_i\alpha_j y_i y_j (x_i \cdot x_j) \tag{11}$$

subject to

$$\sum_{i=1}^{l}\alpha_i y_i = 0 \text{ and } 0 \leq \alpha_i \leq C. \tag{12}$$

Note that the Lagrange coefficient α_i is bound by the tradeoff parameter C. The concept of nonseparable case can be extended to the nonlinear classification problem through mapping of the nonlinear training datasets into a much higher dimensional space, i.e., $x_i \rightarrow \Phi(x_i)$. The nonlinear input space is mapped into the linear feature space so that the data can be separated by the linear optimal hyperplane. The decision function for the optimal hyperplane can be written as

$$f(x) = \sum_{i=1}^{l}\alpha_i y_i(\Phi(x)\cdot\Phi(x_i) + b). \tag{13}$$

The mapping is easily made by a kernel function, $K(x, x_i) = \Phi(x)\cdot\Phi(x_i)$ [20], [21]. The kernel functions to be used in this research can be polynomial function and Gaussian radial basis function (RBF) which are good for predicting nonlinear tag detection rates.

IV. Performance Evaluation

A. Trial-and-Error Experimental Approach

In order to predict the tag detection rate by the proposed intelligent SVM approach, we first need to train the proposed SVM using the raw data (training datasets) obtained through the trial-and-error experimental method described in the previous section.

In this section, we show the results of experiment and analyze them. First, the trial-and-error experiment with 1-ton truck, which is popular in practice, is conducted. A total of six tag positions in the front widow of the mobile vehicle shown in Fig. 1 are tested with different moving speeds of the vehicle and angles of the antennas. The five different speeds tested include 10, 30, 50, 70, and 90 km/h. The tests are made with the bar type antenna. Three different angles, 30°, 45° and 60° are applied for the bar type antenna vertically, as depicted in Fig. 2. There are thus 15 combinations of influence factor conditions for each type of antenna with three angles and five speeds, as shown in Table I: (30°, 10 km/h), (30°, 30 km/h), (30°, 50 km/h), (30°, 70 km/h), (30°, 90 km/h), (45°, 10 km/h), (45°, 30 km/h), (45°, 50 km/h), (45°, 70 km/h), (45°, 90 km/h), (60°, 10 km/h), (60°, 30 km/h),(60°, 50 km/h), (60°, 70 km/h), and (60°, 90 km/h). A total of 30 trials with the mobile vehicle passing through the antennas are conducted for each combination. Tag detectability (detection rate) is a ratio of the number of successful tag detection trials to 30 trials. The rate of successful tag detection by

TABLE I
TAG DETECTABILITY FOR EACH TEST COMBINATION (BAR TYPE)

Angle_Speed Combination	Tag Position					
	A	B	C	D	E	F
(30°, 10k/h)	1	1	1	1	1	1
(30°, 30k/h)	1	1	1	0.7	1	0.4
(30°, 50k/h)	0.4	0.7	0.57	0.17	0.23	0
(30°, 70k/h)	0.1	0.6	0.5	0	0	0
(30°, 90k/h)	0	0.23	0.33	0	0.07	0
(45°, 10k/h)	1	1	1	1	1	1
(45°, 30k/h)	1	1	1	1	0.07	1
(45°, 50k/h)	0.93	1	1	0.7	0.9	0.7
(45°, 70k/h)	0.56	1	1	0.33	0.5	0.23
(45°, 90k/h)	0.07	0.7	0.5	0	0	0
(60°, 10k/h)	1	1	1	0.97	1	1
(60°, 30k/h)	1	1	1	0.33	1	0.67
(60°, 50k/h)	0.67	0.93	0.93	0.17	0.4	0.33
(60°, 70k/h)	0.17	0.7	0	0.33	0.07	0
(60°, 90k/h)	0.07	0.5	0	0	0.03	0

TABLE II
ACCURACY CALCULATION OF RFID TAG DETECTABILITY PREDICTION

Real Tag Detectability %	Predicted Tag Detectability %	Accuracy
100%	100%	Correct
Below 100%	Below 100%	Correct
100%	Below 100%	Incorrect
Below 100%	100%	Incorrect

the RFID reader for each combination is obtained with the tag attached in the respective six positions of the front window.

Table I summarizes the numerical detectability results of the experimentation for the bar type testbed shown in Fig. 2. If the RFID reader reads each tag attached to the six positions correctly, we consider that the tag is detected successfully. Notice from Table I that 30° and 45° antenna angles with the moving speed of the tag of 10 km/h give 100% tag detection rate in all the six positions. We say that the influence factor conditions give a perfect tag detection. 30°, 45°, and 60° with 20 km/h result in a very high rate of detection. It is also noticed that the rate of detection usually decreases as the moving speed of the tag increases. In terms of the antenna angle, 45° is better than the others. With 45°, the tags in positions B and C can be detected, i.e., a perfect tag detection, even with relatively high speed of the vehicle, 70 km/h.

B. Intelligent Prediction Approach Using SVM

1) Kernel Functions in Use and Optimization: The experiment of the trial-and-error method as shown above is very time-consuming and requires substantial amount of manual operation for finding the best influence factor conditions such as antenna angle, tag position, and speed of mobile tag. Therefore, we perform tag detection using the proposed intelligent SVM model. The accuracy of the proposed approach is verified by comparing the results obtained from the proposed SVM prediction model with the results obtained by the experimental (real) approach. Instances of prediction accuracy are illustrated in Table II. Here, SVM$^{\text{light}}$ Version 6.01 [22] is used for operating the proposed SVM model.

The first step is to train the intelligent SVM prediction model using the tag detectability data obtained from the experimental approach mentioned previously. The second step is to let the trained SVM model predict the tag detection rate for the given input variables, i.e., influence factors.

We use two kernel functions such as polynomial function and Gaussian RBF for SVM. The polynomial function kernel is

$$K(x, x_i) = (x \cdot x_i + 1)^d \tag{14}$$

where d is a non-negative integer and the degree of polynomial kernel function. The RBF kernel is

$$K(x, x_i) = \exp\left(\frac{-\|x - x_i\|^2}{2\sigma_i^2}\right) \tag{15}$$

or simply

$$K(x, x_i) = \exp\left(\gamma\left(-\|x - x_i\|^2\right)\right), \quad \gamma \geq 0. \tag{16}$$

A total of 630 training datasets are used to train the proposed SVM model. A total of 234 test datasets are used to verify the prediction accuracy of SVM. For our problem, the training datasets have three input features: antenna angle, mobile tag speed, and tag position and one output shows if the tag is detected or not. A 100% tag readability means that the tag signal strength of all of six tags in Fig. 1 is strong enough to be sensed (detected) by the antenna. If the SVM model predicts that a tag is not detected by the RFID reader, it is classified in below 100% tag detection in the output of the SVM model. Fig. 4 shows the SVM tag detectability prediction model proposed in this paper. There are three input variables, angle of antenna (x_1), speed of vehicle (x_2), and position of tag (x_3). The output variable is predicted detectability (y) that gives either 100% tag detection rate (considered to be "detection") or below 100% (considered to be "no detection"). The input variables and target variable (measured tag detection rate, i.e., measured experimental detectability) pairs of the training dataset determine the unknown parameters of the decision function, $f(x)$ and object function in the decision block. For an example of training, a training dataset pair of measured three input values $x_1 = 45°$ (angle of antenna), $x_2 = 10\ \mathrm{km/h}$ (speed of vehicle), and $x_3 = C$ (position of tag) with measured experimental output $y = 1$ (100% detectability) will be applied to determine all unknown variables of the decision function $f(x)$ allowing to optimize the object function. Given γ and C, a total of 630 training dataset pairs are used to train the proposed model to determine the unknown variables. Once training the model is completed, the trained model is ready to predict the tag detectability in order to explore the unprecedented influential factor conditions.

The prediction accuracy is verified with different kernel degree d of 2, 3, and 4 for the polynomial function kernel, γ value of 0.01, 0.1, 0.5, 1, 5, 10, and 15 for the RBF kernel, and the trade-off parameter, C ranges from 0.01 to 2000 for both the kernel functions. We use the cross-validation to tune the values of parameter of the kernel functions and the tradeoff parameter C allowing an optimal solution [23]. The hybrid algorithm is used for the cross-validation [24]. First, different degrees of the polynomial function are applied with a fixed C value as $\{d = 2, 3, 4 \mid C = 2000\}$. Li *et al.* showed that a relatively large C value of 2000 can work for the most cases [25], [26]. For our problem, with the d value of 3 giving the best result, as shown on the left side in Fig. 5, we proceed with different C values as

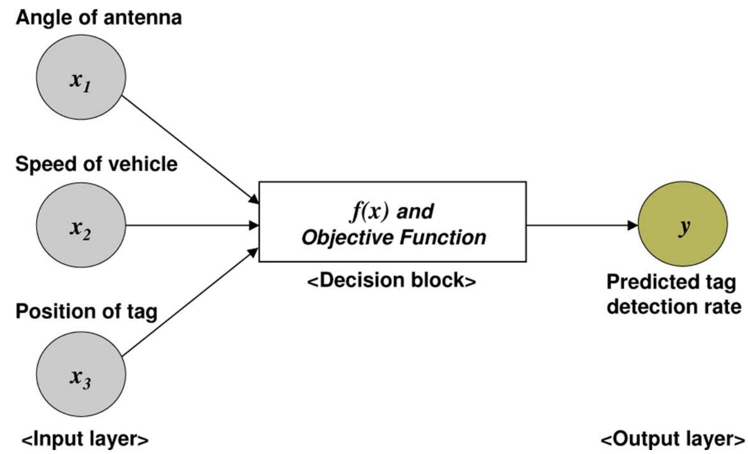

Fig. 4. Proposed SVM tag detectability prediction model.

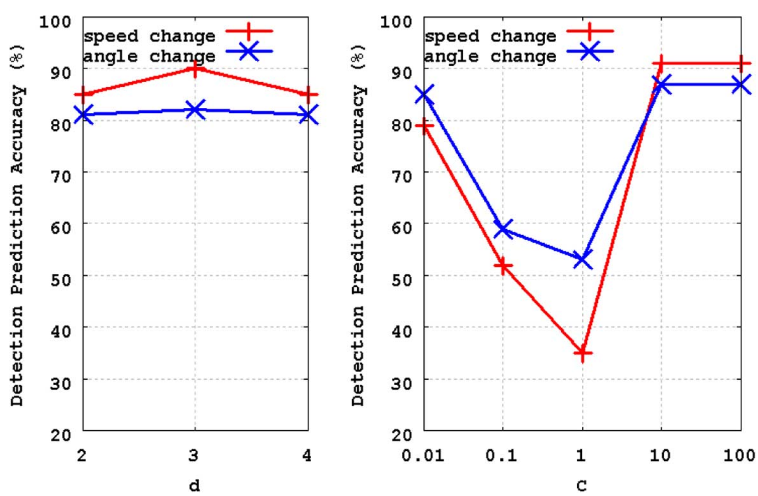

Fig. 5. Prediction accuracy by polynomial kernel function.

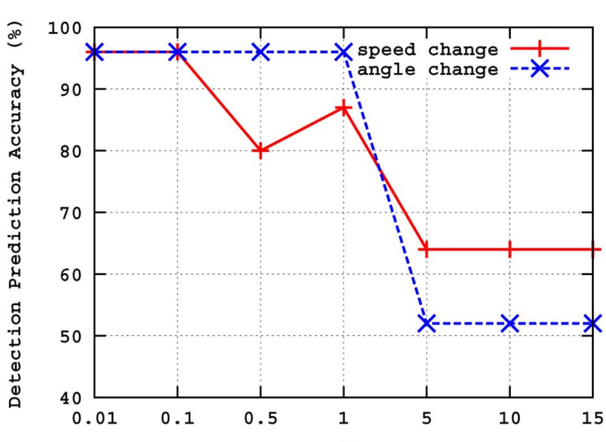

Fig. 6. Prediction accuracy for speed and angle change by RBF kernel function ($C = 2000$).

$\{0.01, 0.1, 1, 10, 100 \mid d = 3\}$ illustrated on the right side in Fig. 5. By the same token, the hybrid-algorithm is applied for RBF kernel: $\{\gamma = 0.01,0.1,0.5,1,5,10,15 \mid C = 2000\}$ shown in Fig. 6, and then $\{C = 1,5,10,50,100,500,1000,2000 \mid \gamma = 0.1\}$.

We verify the prediction accuracy with two different test modes: the speed change and antenna angle change. Fifty-four and 180 test examples are used to verify the prediction accuracy for the speed change and the antenna angle change, respectively. In the speed change mode, three new speeds of 20, 40, and 60 which were never trained before, will be adopted to predict detectability. By the same way, two new antenna angles, 40° and 50° are adopted. The new angles were also never used for training before. These new and never-trained input feature values (influence factor conditions) are difficult to predict and thus they are good to verify the prediction capability of the proposed SVM prediction model. Thus, these newly added influence factor conditions will allow the proposed SVM prediction model to verify the prediction accuracy with more reliability.

2) Results and Analysis: We first conduct the prediction with the polynomial function kernel. Using the hybrid algorithm of cross-validation, the mobile RFID tag detectability is predicted with $d = 2$, 3 and 4, and $C = 2000$. The prediction accuracy is presented on the left side in Fig. 5. X axis stands for degree d. Highest prediction accuracy of 90.74% is obtained for the speed change and 81.67% for the angle change, respectively, when $d = 3$. 85.19% of the prediction accuracy is shown with both

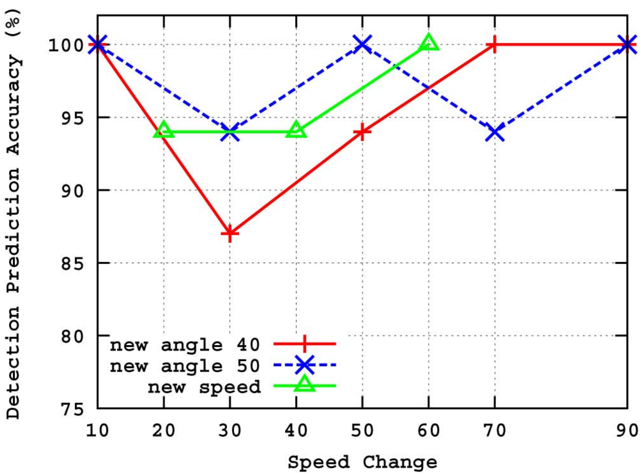

Fig. 7. Prediction accuracy for new vehicle speeds and antenna angles.

$d = 2$ and $d = 4$ for the speed change. 81.11% of the prediction accuracy is shown with both $d = 2$ and $d = 4$ for the angle change. In what follows, thus, we are suggested to further explore prediction of mobile RFID tag detection with $d = 3$ while changing the tradeoff parameter C.

The right side one in Fig. 5 shows the results of prediction accuracy after applying degree d of 3 with variable C values. Fig. 5 shows that C values of 10 and 100 provide the best prediction performance of tag detectability, 90.74% of accuracy for the speed change. C value of 0.01 shows 84.98% of accuracy for the angle change.

We now apply a different kernel function, RBF, for prediction with $\{\gamma = 0.01, 0.1, 0.5, 1, 5, 10, 15 \mid C = 2000\}$ for both the speed change and angle change. In Fig. 6, observe that γ values of 0.01 and 0.1 give the best accuracy of 96.15% in the speed change, which is much better than the polynomial kernel function. We test C values of 1, 5, 10, 50, 100, 500, and 1000 with $\gamma = 0.1$ and 0.01 but they result in the same accuracy of 96.15% as with the C value of 2000.

In the angle change, γ values of 0.01, 0.1, 0.5, and 1 give the best accuracy of 96.67%, as shown in Fig. 6. For the C values of 1, 5, 10, 50, 100, 500, and 1000 with the γ values of 0.01, 0.1, 0.5, and 1, respectively, we obtain the same accuracy as with the C value of 2000.

As mentioned earlier, new speeds of 20, 40, and 60 are applied to test the tag detectability prediction accuracy of the proposed SVM prediction model, and the result is provided in Fig. 7. The prediction accuracy is for the speed of 60 is 100%, while 94.4% for the speed of 20 and 40. Unlike the intuition, accuracy of prediction is changed at least up to a certain level. Fig. 7 also shows the prediction accuracy with the new antenna angle of 40° and 50°. Notice that the tag detectability prediction accuracy is 100% for several speed and antenna angle values.

Thus only for the case of 100% prediction accuracy, we can see whether or not a tag can be detected under the new influence factor conditions of angle and speed with predicted detectability instead of trial-and-error operations. If the predicted detectability of a tag is “1,” we might conclude that the new influence factor conditions are desirable for the mobile RFID system. On the other hand, if below “1” such as 0.9, 0.95, and so on, the new influence factor conditions cannot be suggested.

V. Conclusion

Even though it is crucial to find the best influence factor conditions for detecting mobile RFID tag using RFID reader, very few researches have been done in this area so far. RFID tag detection becomes more challenging when the tag is moving at high speed. We have carried out comprehensive experiment to extract training datasets under different conditions such as speed of moving tag, angle of antenna, and position of tag. We showed that mobile RFID tag detectability is significantly influenced by the influence factor conditions. Also an efficient model predicting tag detectability has been proposed as an alternative for the traditional time consuming trial-and-error method in this paper.

The proposed intelligent prediction model is based on SVM. Extensive simulation has been conducted to verify the prediction accuracy of the proposed method. The results show very high accuracy in both the speed change and angle change. Thus, the proposed intelligent prediction approach can possibly be applied at the deployment stage. Even though the tag detectability prediction approach research for mobile RFID is at the very first stage, it is very meaningful to give an alternative for the traditional time consuming trial-and-error method. Thus, we need to add more influence factors to the proposed prediction model in order to be well applied in industry in the future. We plan to carry out more studies with different influence factors such as relative height and distance of antenna, various number of antennas, moving direction of the tags, antenna type, material of object, and so on.

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