Orthogonal Resource Allocation Using SVM for CSMA/CA

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***Abstract*—Due to the wide spread of machine-to-machine (M2M) communications and Internet-of-things (IoT), large number of wireless terminals are densely deployed. Under such dense deployment, it is necessary to manage the mutual interference among wireless terminals. Carrier-sense multiple access/collision avoidance (CSMA/CA) is one of the random access schemes that allow wireless terminals to access a channel while avoiding such mutual interference. However, if two wireless terminals are in the hidden terminal relation, a packet collision may happen as the carrier sense mechanism does not work. This results in the degradation of packet delivery rate (PDR) performance. Whether or not particular two wireless terminals are in the hidden terminal relation is an unobservable information from a network controller such as an access point (AP). In this paper, we tackle this problem by using machine learning. By using machine learning, the wireless controller makes a guess of the unobservable information from the observable information. We will use the wireless terminal locations and received signal strength at APs as the observable information. Based on the estimated unobservable information, the wireless controller assigns orthogonal resources to the wireless terminals that are in the relationship of hidden terminal in order to avoid the packet collision. Numerical results confirm that the proposed approach can improve the PDR performance up to 15% compared to the random resource allocation scheme.**

I. INTRODUCTION

The demand for larger capacity in wireless communications is fast growing due to the rapid spread of multimedia communications and social networking services. Furthermore, the emerge of the machine-to-machine (M2M) communications for Internet-of-Things (IoT) adds more demand for larger capacity. A large number of wireless terminals need to share the limited resources while achieving desired quality-of-service (QoS). In order to achieve it, it is mandatory to handle the deterioration of signal due to the channel and the mutual interference among wireless terminals by means of advanced techniques such are resource scheduling and spatial beamforming. However, these techniques require the accurate channel state information (CSI), which usually needs to be fed back from wireless terminals to the network controller.

To avoid the explicit feedback for resource allocation, machine learning based resource allocation schemes have been proposed in [2] and [3]. The objective of machine learning for resource allocation is to estimate "*unobservable information*" from "*observable information*". The unobservable information can be collected by additional feedback or sensor node in advance. Then the relationship between the unobservable information and the observable information is then learned by machine learning. By this, resource allocation can be performed based on the unobservable information once the learning process is completed.. In [2] and [3], a cell selection problem and the optimal beamforming weight selection problem in a heterogeneous network are talcked by machine learning.

In this paper, we focus on carrier-sense multiple access/collision avoidance (CSMA/CA) which is one of the random access protocols [1]. In CSMA/CA, each wireless terminal monitors the wireless medium to check whether or not there is ongoing transmission. If the wireless terminal does not hear any active transmission, it starts transmission following the predefined procedure. However, due to the large distance or obstacles between the wireless terminals, the wireless terminal may not be able to hear the active transmission even though there is indeed ongoing transmission. This is known as "hidden terminal problem". If such situation occurs, the packet collision happens and this results in the degradation of packet delivery rate (PDR) performance. In order to avoid the packet collision due to the hidden terminal, we propose to allocate the orthogonal resources to the wireless terminals that cannot sense each other. Since the information whether or not the particular two wireless terminals are in the relation of hidden terminal is "unobservable information" from the network controller, we propose to apply machine learning. The network controller guesses if the particular two wireless terminals can sense each other ("unobservable information") from "observable information" such as the locations of wireless terminals and the received signal strength at the access points (APs).

The rest of the paper is organized as follows. In Sect. II, we briefly review the related works. In Sect. III, the proposed machine learning based resource allocation scheme is introduced. In Sect. IV, the computer simulation results are provided. Sect. V concludes the paper.

II. RELATED RESEARCH

In [2], [3], the machine learning has been successfully introduced into the heterogeneous cellular network where macro/control base station (BS) assigns one of small BSs to each wireless terminal for data transmission. The channel between the macro BS and the terminal is taken as "observable information" while the channel between the small BS and the terminal as "unobservable information". The channel model is assumed to be geometric stochastic channel model (GSCM) [4]. In this channel model, the channel response between a transmitter and a receiver is determined by their locations. Since the location of the macro BS and the small BS are fixed, the channel responses are solely determined by the location of the terminal. It indicates that there is a one-to-one mapping from the location of terminal to the channel response. Thus, the channel responses can be expressed as

$$\begin{cases} \mathbf{h}_{\mathrm{o}} = g_{\mathrm{o}}(\mathbf{x}) \\ \mathbf{h}_{\mathrm{u}} = g_{\mathrm{u}}(\mathbf{x}) \end{cases}, \tag{1}$$

where $\mathbf{x}$ denotes the location of the terminal, and $\mathbf{h}_{\mathrm{o}}$ and $\mathbf{h}_{\mathrm{u}}$ denotes the observable channel between the macro BS and the terminal and the unobservable channel between the small BS and the terminal, respectively. In (1), the functions $g_{\mathrm{o}}(\cdot)$ and $g_{\mathrm{u}}(\cdot)$ are the one-to-one mapping functions. Since those functions are one-to-one mapping functions, they can be inversed such as $\mathbf{x} = g^{-1}(\mathbf{h}_{\mathrm{o}})$. Thus, the unobservable channel response $\mathbf{h}_{\mathrm{u}}$ can be expressed as a function of the observable channel response $\mathbf{h}_{\mathrm{o}}$ as follows:

$$\mathbf{h}_{\mathrm{u}} = g_{\mathrm{u}}(g_{\mathrm{o}}^{-1}(\mathbf{h}_{\mathrm{o}})). \tag{2}$$

By using the machine learning such as neural network (NN) [5], the mapping from the observable channel to the unobservable channel can be learned. After learning process is completed, the unobservable channel response can be estimated from the observable channel response.

A. Optimal Cell Selection [2]

In [2], the NN has been introduced to assign the small BS to each terminal. In order to determine which small BS should be assigned to each terminal for data transmission, it is necessary to estimate the channel response between each small BS and each terminal. However, this incurs huge overhead to the system. To avoid such overhead, NN is used to estimate the channel condition between each small BS and each terminal without incurring the overhead. The channel condition between each small BS and the terminal is estimated from the channel between macro BS and the terminal based on (2). Computer simulation results show that it is possible to select the optimal small BS with up to 74% accuracy.

B. Optimal Beam Forming Selection [3]

For upcoming next generation wireless communications systems, it is expected to utilize mmWave frequency band as it can provide wider frequency bandwidth. However, due to the large propagation loss, it is unavoidable to use massive multiple-input multiple-output (MIMO) together with mmWave transmission. In order to fully utilize the benefit of massive MIMO, it is essential to select the proper beamforming weights. This requires the huge amount of overhead. In [3], the two-step optimal beamforming selection scheme based on NN is proposed. At each small BS, a finite number of beamforming weights are prepared. By using NN, the control BS selects the one beamforming weights based on the observable channel response between the control BS and terminal. By computer simulation, it has been shown that the proposed beamforming selection scheme can select the optimal beamforming weight with 99.97% accuracy.

III. Orthogonal Resource Allocation Using Machine Learning

In this section, we briefly introduce the basic operation of CSMA/CA and support vector machine (SVM) [5]. After that, we introduce the proposed scheme which consists of two steps, (1) carrier sense (CS) learning using SVM and (2) resource allocation with CS possibility information, which is either 0 or 1 to indicate whether or not the two particular terminals can CS each other.

A. CSMA/CA

If multiple wireless terminals access the wireless medium randomly, the transmitted packets may collide with each other. In that case, the wireless terminal needs to retransmit the same packet, so it incurs the spectrum efficiency degradation. In CSMA/CA, each wireless terminal senses the wireless medium before it starts packet transmission. If the wireless terminal CS the ongoing transmission, it waits for the transmission. Otherwise, it starts packet transmission. However, due to the obstacles and the distance among the wireless terminals, the wireless terminals may not be able to CS each other. This problem is known as "hidden terminal problem". One of the solutions to this problem is request-to-send/clear-to-send (RTS/CTS) protocol. In RTS/CTS protocol, a wireless terminal transmits RTS packet to AP in prior to data packet transmission and then AP returns CTS packet in order to approve the data packet transmission. By this, the wireless terminal that is in the hidden terminal relation of the wireless terminal of interest can recognize the ongoing transmission. However, this protocol requires additional overhead for RTS/CTS message exchange.

B. SVM

SVM is one of *supervised learning algorithms* that classify the input data sets by learning the relation between the feature value and the learning label. The feature value is the input value to learning engine and the learning label is the output corresponding to each input feature value. In this paper, we adopt the location information and the received signal strength as the input feature value. For learning label, the possibility of CS is adopted.

In SVM, the decision boundary is generated from the given training data sets which maximizes *margin*. The margin is defined as the distance between the decision boundary and the data belonging to each label that is closest to the decision boundary.

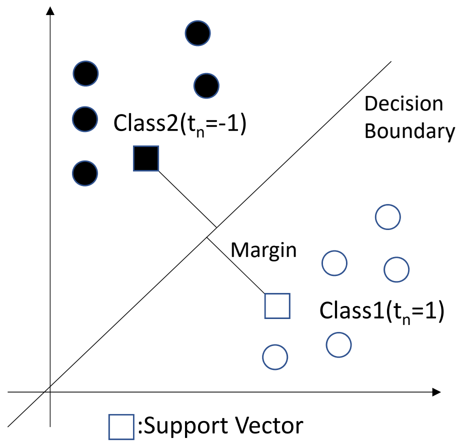


Fig. 1. Support Vector and Margin Maximization

C. Learning for CS Possibility Estimation using SVM

1) Learning Model: In the proposed scheme, location information of terminal and received signal strength indicator (RSSI) information are used as a feature value. We assume that the information is ideally estimated at APs. For SVM, different kinds of kernel functions can be used to transform the input information into the feature values, which are input to SVM. The kernel functions are represented as inner product with two feature values. By this, SVM can make a nonlinear decision boundary. As kernel functions, the following linear kernel and gauss kernel are used:

$$\begin{cases} k_{\mathrm{lnr}}(\mathbf{x}_n, \mathbf{x}_m) = \mathbf{x}_n^T \mathbf{x}_m \\ k_{\mathrm{gs}}(\mathbf{x}_n, \mathbf{x}_m) = \exp(-\frac{\|\mathbf{x}_n - \mathbf{x}_m\|^2}{2\sigma^2}) \end{cases}, \tag{3}$$

here $\mathbf{x}_n$ is the feature column vector whose element is feature value such as the location of the terminal in (1). Kernel function works on the pair of two feature vectors. In learning phase, pair of two terminals are distributed randomly and uniformly in simulation area, and those input-feature values and learning label are utilized to generate the decision boundary of SVM. In estimation phase, J terminals are distributed randomly and uniformly in the same simulation area, CS possibility among each pair of terminals are estimated by the learned decision boundary.

2) Generation of Multiple SVM: In the proposed scheme, it is necessary to estimate CS possibility using observable information between two terminals which are located randomly. If one of the two terminals is fixed, one SVM can estimate with high accuracy. But, if two terminals are located randomly, estimation accuracy severely degrades because the input feature values to SVM significantly vary. Therefore, in this paper, we propose to split the simulation area into multiple grids as shown in Fig. 2. In each grid, one SVM is created. One of SVMs is selected based on the location or RSSI of terminal 1. Grid selection with different feature value is explained below:

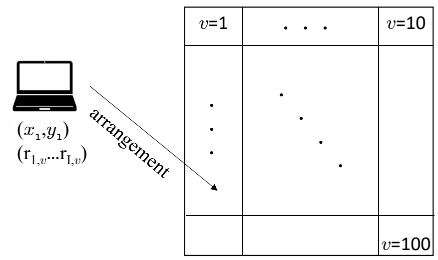


Fig. 2. Splitting to grid and arrangement

- Using location information: Grid index v is calculated using location of terminal 1 as follows:

$$v = \mathrm{floor}(\{x_1 + (y_1 * D)\}/G), \tag{4}$$

  where x_1 and y_1 are the x and y locations of terminal 1 , respectively, and D is the width of simulation area, and G is the width of grid.
- Using RSSI information: Grid index is determined as follows:
  1) An anchor terminal is placed at the center of each grid and the reference RSSI value between each AP and it is calculated.
  2) Each AP calculates the RSSI value between it and terminal 1.
  3) The absolute value of the difference between the reference RSSI value and the RSSI value is calculated and sorted in ascending order.
  4) Set $i = 1$
  5) Each AP chooses the grid that has the ith minimum value in (3) and reports to the controller.
  6) The grid being reported most is chosen.
  7) If there are multiple grids that reported most, set $i = i + 1$, and repeat above until only one grid is determined.

The AP allocates the orthogonal resources to each terminal by the upper layer based on the CS possibility information obtained in Sect. III.C. Let us assume that the number of orthogonal resources is K.

1) For each terminal, the number of other terminals that cannot be CSed by the terminal of interest is counted.
2) The number counted in 1) is sorted in descending order.
3) From the top to the bottom, AP allocates the $K-1$ orthogonal resources.
4) For the remaining $J-K+1$ terminals, the same resources are assigned.

By the above process, the terminals that have more number terminals that cannot CS are assigned to the orthogonal resources. This can reduce the packet collision due to the hidden terminal problem. Although remaining $(K-J+1)$ terminals use the same resource, they may be able to avoid the packet collision by CS. In this research, we adopt time division multiple access (TDMA) based resource allocation.

TABLE I
SIMULATION PARAMETERS

Number of terminals J	3
Number of orthogonal resources K	2
Noise power density	-174 [dBm/Hz]
Bandwidth	10 [MHz]
CS threshold	-82.0 [dBm]

TABLE II
RECEIVE THRESHOLD

SNR	Γ[dB]
$4\leq$ SNR <6	4
$6\leq$ SNR <8	6
$8\leq$ SNR <10	8
$10\leq$ SNR <12	10
$12\leq$ SNR <16	12
$16\leq$ SNR <20	16
$20\leq$ SNR <21	20
$21\leq$ SNR	21

In other words, each terminal transmits based on CSMA/CA only in one of the time frames that is assigned by AP.

IV. SIMULATION RESULTS

A. System Model

Table I shows the simulation parameters. The uplink transmission is considered where J terminals transmit data packet to K APs. The terminals are located randomly and uniformly within the simulation area. For channel model, we adopt two different scenarios: 1) the distance dependent pathloss + spatially correlated shadowing model [6], 2) ray tracing model using Raplab software [7]. For simplicity, each terminal transmits data packet with a probability of 0.8. If multiple terminals transmit packets to AP using the same resource, the packet collision happens. At each AP, if the signal-to-interference plus noise ratio (SINR) of one terminal is higher than the threshold Γ, the packet is assumed to be successfully received. Since adaptive modulation is assumed, the threshold value for required signal power changes based on the selected modulation scheme as shown in Table II. In this paper, we adopt the packet delivery rate (PDR) as a performance metric, which is defined as

$$\mathrm{PDR} = D/S, \tag{5}$$

where D is number of packets that is successfully received by at least one AP and S is the number of packets transmitted from all terminals.

B. Evaluation in Spatially Correlated Shadowing Model

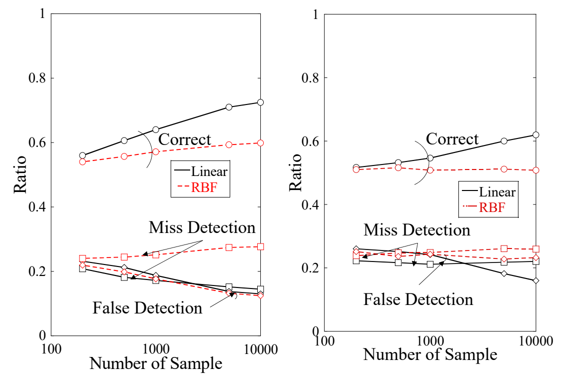
1) Model of Shadowing Model: In this model, received power of a terminal at AP is represented as:

$$P_{\mathrm{r}} = P_{\mathrm{t}} - 10\alpha\log_{10}d - \beta - 10\gamma\log_{10}f - \eta \tag{6}$$

where P_{r} is received power, P_{t} is transmit power, d is distance between terminals [m], f is carrier frequency [GHz]. And, η is log-normally distributed shadowing loss with zero-mean and standard deviation of σ [dB] and is assumed to have correlation

TABLE III
CHANNEL PARAMETERS(SHADOWING MODEL)

Number of SVMs	1,100,400
Transmit power P_{t}	10.0[dBm]
Carrier frequency f	2.4[GHz]
Simulation size	100×100[m^2]
Coefficient of Propagation loss with distance α	3.5
Coefficient of Propagation loss with frequency γ	1.96
Coefficient of Propagation loss with constant β	28.6
Shadowing deviation	6.0[dB]
Number of Shadowing Grids	20×20
Number of learning data	200,500, 1000,5000,10000
Number of test data	100000



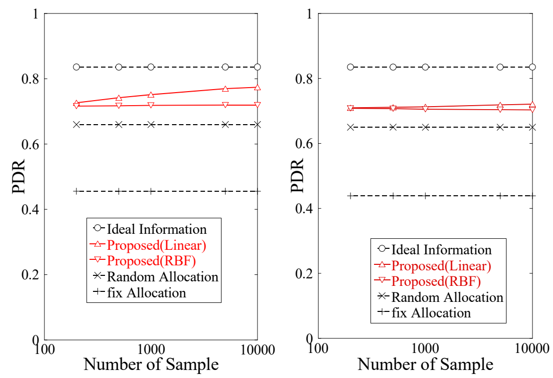
(a) location information (b) Power information

Fig. 3. Estimation accuracy

among the adjacent locations [6]. Channel parameters are listed in TableIII. Furthermore, in this simulation setup, the number of grid in each axis is set to 10, i.e., there are 100 grids for SVM in total.

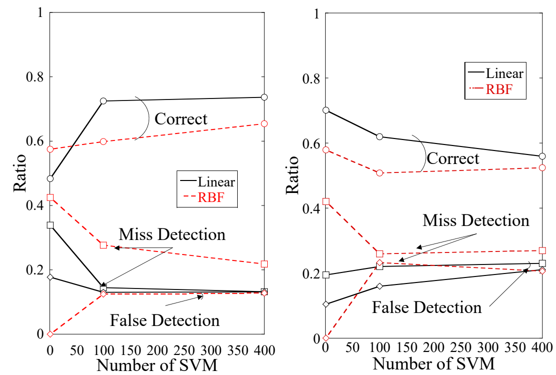
2) Estimation Accuracy: Fig. 3 shows the estimation accuracy of the proposed scheme with linear kernel and gauss kernel. For performance evaluation, the correction estimation probability, the false detection probability, and the miss detection probability are considered. The false detection probability is the probability that SVM estimates the pair of terminals can carrier sense each other although they actually cannot. The miss detection probability indicates the probability that SVM estimates that the pair of terminals cannot carrier sense each other although they actually can carrier sense each other. As the figure clearly shows that estimation accuracy improves as the number of training data sets increases. The proposed scheme can estimate CS possibility with an accuracy of about 80% with the location information being the feature values. On the other hand, although the estimation accuracy improves with RSSI information, it is lower than when location information is utilized. This is because of Although SVM is targeted to continuous value, Shadowing loss is spatially discrete.

3) PDR: the average PDR performance of the proposed scheme is shown in Fig. 4. For comparison, the performances of the case when CS possibility is ideally estimated, the



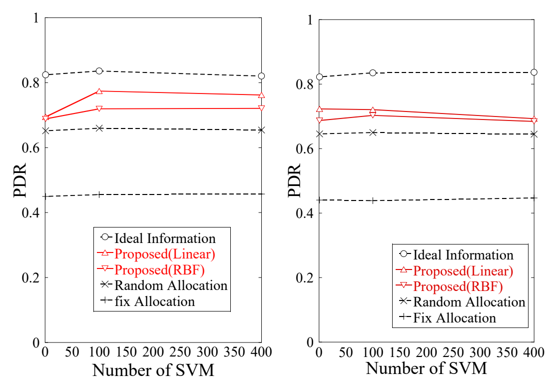
(a) location information (b) Power information

Fig. 4. PDR



(a) location information (b) Power information

Fig. 5. Estimation accuracy with the number of grid



(a) location information (b) Power information

Fig. 6. PDR with the number of grid

random resource allocation, and the fixed resource allocation are shown. In the random resource allocation, each terminal is randomly assigned to resource. In the fixed resource allocation, all the terminals are assigned to the same resource. From the results, it is shown that the average PDR performance improves as the number of training data sets increases. The average PDR of about 80% can be achieved with the number of training data sets of 10,000. This is about 15% higher than the random resource allocation which does not utilize the unobservable information. The performance degradation from the ideal CS possibility estimation is about 6%. When the RSSI information is utilized, the average PDR performance degrades due to the low estimation accuracy of CS possibility estimation.

4) Impact of Grid Size: So far, it has been shown that the average PDR performance improves as the number of training data sets increases for the given grid size. Figs 5 and 6 show the impact of the grid size on the estimation accuracy and the average PDR performance of the proposed scheme. The number of training data set is set to 10,000. From these results, the estimation accuracy improves as the grid number increases with location information. On the other hand, the performance degrades as the grid number increases when RSSI information is adopted. This performance degradation is due to the grid allocation scheme used in this research. For grid decision, each AP selects one grid independently. This suggests necessity of cooperative grid decision scheme.

C. Evaluation in Ray-tracing Model

1) Ray-Tracing Model: In this model, received power, delay, phase shift of the transmitted signal are calculated using Ray-tracing from transmitter. Terminals are placed at every one meter. The indoor layout model used in this simulation is shown in Fig. 7. The number of grid is set to 1. Channel parameters are listed in Table IV. The PDR performance is always 1 when the transmit power is set to 10 [dBm]. Thus, in this subsection, the impact of the transmit power below 10 [dBm] on the PDR performance is evaluated.

2) Estimation Accuracy: Fig. 8 shows the estimation accuracy of the proposed scheme with linear kernel and gauss kernel. As the figure shows that estimation accuracy is improved by the proposed scheme irrespective of the transmit power. The proposed scheme can estimate CS possibility with an accuracy of over 80% irrespective of the information used for the feature values. Although estimation accuracy using RSSI information is lower than that using location information in shadowing model, estimation accuracy using RSSI information is close to that using location information in ray-tracing model. This is because of correlation between positions. As ray-tracing model calculates channels continuously, this continuous feature value improves estimation accuracy. When transmit power is -20 [dBm], estimation accuracy is low. This is because the received power is close to CS threshold, so CS possibility fluctuates with small change of locations when transmit power is -20 [dBm].

3) PDR: Fig.9 shows the average PDR performance of the proposed scheme. From the results, it is shown that the average PDR performance is higher than the random allocation. When transmit power is -20[dBm], the PDR performance is about

TABLE IV
CHANNEL PARAMETERS(RAY-TRACING MODEL)

Number of SVMs	1
Transmit power	10,0,-10,-20,-30[dBm]
Carrier frequency	5.0[GHz]
Simulation size	7×7[m^2]
Number of learning data	177
Number of test data	1593

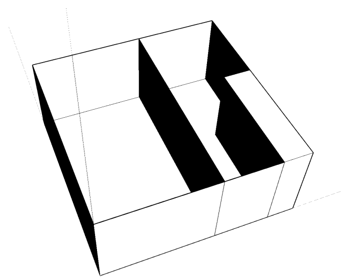
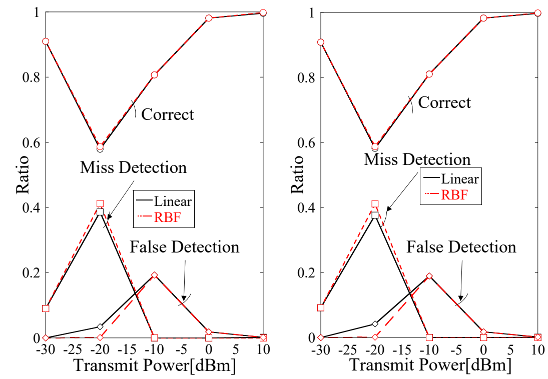
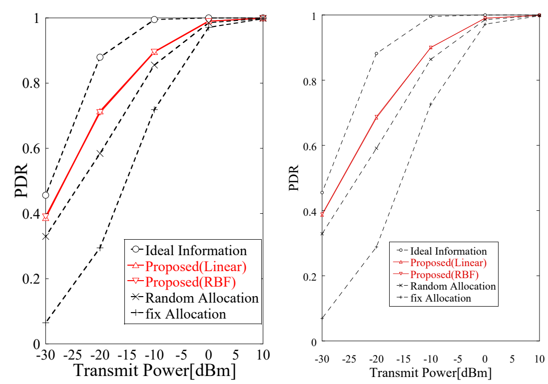


Fig. 7. layout model in ray-tracing model



(a) location information (b) Power information

Fig. 8. CS estimation accuracy



(a) location information (b) Power information

Fig. 9. PDR

10% higher than random allocation scheme. Although the PDR performance using RSSI information is lower than that using location information in shadowing model, the PDR performance using information is close to that using location information in ray-tracing model. This is because of improvement of estimation accuracy in ray-tracing model as discussed above.

V. CONCLUSION

In this paper, we have proposed resource allocation scheme to avoid interference from hidden terminal in CSMA/CA protocol. By SVM, CS possibility is estimated and orthogonal resource allocation is performed based on that estimation. The performance of the proposed scheme was evaluated using correlated shadowing model and ray-tracing model and compared with some other schemes. Numerical evaluation has shown that the proposed scheme can achieve about 80% estimation accuracy and 80% PDR. This is about 15% higher than the random resource allocation scheme.

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