MAC Protocol Identification Using Support Vector Machines for Cognitive Radio Networks

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Abstract

Cognitive radio is regarded as a potential solution to address the spectrum scarcity issue in wireless communication. In CR, an unlicensed network user (secondary user) is enabled to dynamically/adaptively access the frequency channels considering the current state of the external radio environment. In this article, we investigate the medium access control protocol identification for applications in cognitive MAC. MAC protocol identification enables CR users to sense and identify the MAC protocol types of any existing transmissions (primary or secondary users). The identification results will be used by CR users to adaptively change their transmission parameters in order to improve spectrum utilization, as well as to minimize potential interference to primary and other secondary users. MAC protocol identification also facilitates the implementation of communications among heterogeneous CR networks. In this article, we consider four MAC protocols, including TDMA, CSMA/CA, pure ALOHA, and slotted ALOHA, and propose a MAC identification method based on machine learning techniques. Computer simulations are performed to evaluate the MAC identification performance.

Introduction

The emergence of new wireless communication systems, including digital video broadcasting (DVB), wireless local area networks (WLANs), and wireless metropolitan area networks (WMANs), leads to significant increases in the demand for radio resources, resulting in spectrum shortage. However, according to Federal Communications Commission (FCC) records [1], a large portion of the spectrum resources allocated to licensed network users (primary networks) are underutilized. Cognitive radio (CR) [2, 3] is thus implemented to improve spectrum utilization by enabling CR users to access a spectrum hole, which is defined as a frequency band that has been allocated to a licensed network users but is unused at a particular time [4].

A CR is an intelligent radio that has the ability to reason and achieve the specific tasks in radio-related domains [2, 4], which implies that CR users are able to learn from external radio environments and adaptively change their transmission protocols and parameters according to the learning results during their transmissions. This ability is characterized by observation and adaptability. The observation characteristic implies that the CR can observe the radio environment (i.e., spectrum sensing [5], channel estimation, and modulation type identification). The adaptability characteristic means that the CR is able to change its communication methods and parameters based on its observation results (i.e., channel allocation, power allocation [6], modulation and coding scheme selection [7], and waveform adaptation) to adapt to the radio environment. Note that the radio environment observations discussed above relate to the physical layer of a communication network, and this article explores observation of the radio environment in terms of medium access control (MAC) protocols, which provides the potential benefits for CR network performance improvement.

In this article, we investigate the MAC protocol identification, identifying the MAC protocol types and MAC layer parameters, considering time-division multiple access (TDMA), carrier sense multiple access with collision avoidance (CSMA/CA), slotted ALOHA, and pure ALOHA networks. The received power and channel state features are extracted and used to perform MAC protocol identification. Support vector machines (SVMs) are used as the machine learning technique to perform the identification [8, 9].

The remainder of this article is organized as follows. We introduce the SVM and its applications in CR. We describe the applications and benefits of using MAC protocol identification. The feature selection issue is presented. Experiments and results are shown, and finally, we give the conclusion.

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SVMs and Their Application in Cognitive Radio

Support Vector Machines

Support vector machines are machine learning methods that can be used to separate two classes of data [10, 11] by finding an optimal hyperplane. Usually, an SVM conducts an N-dimensional hyperplane, which optimally separates the data into two categories in the feature space, for the input data and patterns. Therefore, points on a two-dimensional feature space can be separated by a line, and points in a three-dimensional feature space can be separated by a plane. Similarly, N-dimensional data points can be separated by an $(N - 1)$-dimensional hyperplane. In SVMs, each input instance, $\mathbf{x}$, is represented by a pair (x_i, y_i), where $x_i \in \mathbb{R}^n$ is the data instance, and y_i is the binary class label (positive or negative). The hyperplane can be written as

$$\mathbf{w} \cdot \mathbf{x} + b = 0, \tag{1}$$

and the classifier is defined as

$$\begin{aligned} &\mathbf{w} \cdot \mathbf{x} + b \geq 1; \\ &\mathbf{w} \cdot \mathbf{x} + b \leq -1, \end{aligned} \tag{2}$$

where $\mathbf{w}$ is the weighing vector and b is a constant. The SVM is hence to solve the optimization problem by maximizing the margin of the classifier while minimizing the sum of errors, which is written as

$$\min \frac{1}{2}\|\mathrm{w}\|^2 + C\sum_{i=1}^{m}\xi_i; \tag{3}$$

subject to
$y_i\,(\mathbf{w} \cdot \mathbf{x_i} + b) \geq 1 - \xi_i,\ \xi_i \geq 0,\ i = 1, 2, \cdots, m;$

where C is a positive constant and ξ_i is the slacks. This optimization problem is then solved by applying Lagrange multipliers and Karush-Kuhn-Tucker conditions.

If the data in its original data space are linearly separable, the SVM is able to find an optimal hyperplane to separate them. However, when the data points are not linearly separable in the data space, the SVM handles this by using a kernel function to map the data to a transformed feature space where a hyperplane is then used to separate them. By using the kernel function, every dot product is replaced by a nonlinear kernel function. The transformation may be nonlinear, and thus the classifier may be nonlinear in the original feature space. There are three types of popular kernel functions:

Linear kernel:
$$K(x_i, y_j) = x_i^T x_j; \tag{4}$$

Polynomial kernel:
$$K(x_i, y_j) = (\gamma x_i^T x_j + r)^d,\ \gamma \geq 0; \tag{5}$$

Gaussian radial basis kernel (RBF):
$$K(x_i, y_j) = e^{-\gamma\|x_i - x_j\|^2},\ \gamma \geq 0, \tag{6}$$

where x_i, y_j are arbitrary instances in the data space, and γ, r, and d are kernel parameters.

SVMs in Cognitive Radio

A CR is a smart radio that has the ability to perform machine intelligence when it opportunistically reuses radio resources [12, 13]. Reference [14] provides a comprehensive study of current machine learning techniques in CR. The SVM, as a state-of-the-art machine learning technique, has been widely used as the pattern classification/recognition techniques for spectrum sensing, modulation classification, user identification, and power allocation in CR. In [15], the learning capability of a CR is fully studied, and it proposes a general learning-based decision making framework considering the CR communication scenario. The least-squares SVM is then demonstrated in detail. In [5], a pattern-classification-based cooperative spectrum sensing algorithm is proposed. In the proposed algorithm, the received signal strengths are treated as features by the CR users and used to detect the spectrum availability by using SVMs, which increases the detection probability while reducing the false alarm probability.

If the data in its original data space are linearly separable, the SVM is able to find an optimal hyperplane to separate them. However, when the data points are not linearly separable in the data space, the SVM handles this by using a kernel function to map the data to a transformed feature space where a hyperplane is then used to separate them.

Use of MAC Protocol Identification

Spectrum Holes v.s CR Transmissions (Frequency-Time Pattern)

Spectrum holes are frequency bands that have been allocated to licensed network users but are not used at a particular time. Therefore, each spectrum hole has a certain frequency range and time duration in the frequency-time domain. In CR, the frequency range and time duration are considered as channel access parameters (i.e., spectrum hole patterns) when a CR user attempts to utilize this spectrum hole. Usually, spectrum sensing determines the frequency range of a spectrum hole; however, the time range information may not be available and is not utilized. We notice that a MAC protocol identification helps each CR user adapt its transmission to match the time pattern of a spectrum hole, which aims to tailor its packet transmission duration to fit the time range of a spectrum hole. This approach enables CR users to make the best use of each spectrum hole and guarantee that there is no interference to primary users (PUs). An example is shown in Fig. 1, where a licensed channel (channel 2) is time slotted, and each unused slot is a spectrum hole for CR users. In the figure, the transmissions of CR user 1 and CR user 3 do not apply the MAC protocol identification; therefore, they have no information on the time pattern of each spectrum hole. As a result, the packet transmission duration optimization cannot be performed. As illustrated in the figure, CR user 1's packet transmission duration is shorter than the duration of the spectrum hole, which results in underutilization of the spectrum hole. On the other hand, CR user 3's transmission duration is longer than the duration of the spectrum hole and collides with the primary transmission, which results in interfering with the PU. In CR user 2's transmission, MAC protocol identification is applied to optimize the time duration of its packet transmission. With spectrum sensing, a CR transmission can be tailored to match the frequency-time pattern of a spectrum hole, which makes full use of the spectrum holes in the time slotted primary networks [16].

Minimize Interference to Reactive Primary Users

Most research on CR networks assume that the users in primary networks are non-reactive (e.g., TDMA), and thus the primary transmission processes are not affected by the presence and transmission of CR users, which means that simultaneous transmissions of CR users can only cause interference and potential data loss while not changing the internal operation state of the PU. However, in a reactive primary network (i.e., a network with CSMA/CA or 802.11 primary users), the presence and transmission of CR users will change the internal operation state of the PUs such as the size of the backoff window, and thus seriously interfere with the primary transmissions [17]. For example, we assume that a primary network uses 802.11. When the PUs are not transmitting, this spectrum hole is used by a CR user. During the transmissions of this CR user, the PUs may have packet arrivals and begin to sense the channel. These PUs need to randomly back off their transmission because the channel is currently used by CR users. When the CR user completes a packet transmission, this channel may be sensed idle due to the PU's backoff mechanism. Therefore, the CR user could start its second packet transmission and, as a result, seriously interfere with the PU. To minimize the interference with the reactive PUs, MAC identification is required to determine the MAC protocol type of a primary network, and then coexisting CR access schemes [17] can be used accordingly.

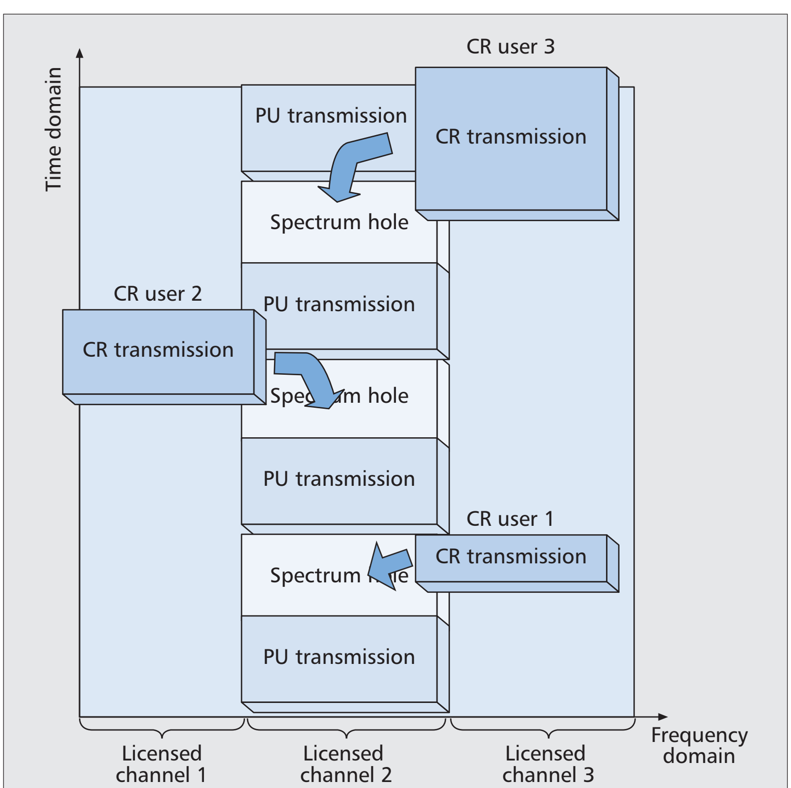

Figure 1. *CR transmissions allocated to spectrum holes*

Communications among Heterogeneous CR Networks

MAC protocol identification is needed when different CR networks are implementing joint communications. According to Mitola's cognitive cycle, a potential way to implement joint communication is described as "observe other network," "learn other network," and "join their communication." This approach implies that each CR network has the ability to observe other CR networks' characteristics (MAC protocols, modulation type, etc.), learn gradually, and finally joint their communication. As illustrated in Fig. 2, there are three separate CR networks labeled CR network 1, CR network 2, and CR network 3 using TDMA, ALOHA, and 802.11 (CSMA/CA), respectively. We assume that the three CR networks are formed independently and do not initially know each other. In this circumstance, MAC protocol identification provides the potential to enable joint communications among them. Consider that CR network 3 attempts to communicate with CR network 1 as an example; the users in CR network 3 must observe and learn about CR network 1 first. Once they get the identification result that CR network 1 uses TDMA, they can implement joint communication through the reconfigurable/adaptive MAC, in which the 802.11 MAC component acts as a local access point within network 3, while the TDMA MAC component acts as a wireless backhaul [18]. When CR network 1 and CR network 3 implement joint communication, the 802.11 packets are gathered in CR network 3 through the 802.11 MAC component, then queued and broadcasted to CR network 1 through the TDMA MAC component. This illustrates that one of the key technique used in heterogeneous CR network communications is MAC identification.

Feature Selection

The four types of MAC protocols, TDMA, CSMA/CA, pure ALOHA, and slotted ALOHA, are illustrated in the time domain in Fig. 3. In the figure, each block represents one packet transmission. The dotted blocks represent the successfully transmitted packets without collision with other users. The shadowed blocks represent the failed transmission packets, which means that more than one network user are transmitting their packets at the same time and therefore result in packet collision. The blank areas, which may or may not be integral times of the block length, represent the duration in which there is no packet transmission and the channel state is idle. In feature selection, a CR user will sense the channel state and sample the received power. Since each of the four MAC protocols has a unique channel access and collision characteristic, the sampled received power mean, power variance, and channel busy state duration, as well as channel idle state duration, will be used in SVMs to implement MAC protocol identification.

In this section, we first investigate one-vs.-one MAC protocol classification, which means to separate two MAC protocols from each other by using the power features (i.e., received power mean, power variance) or time features (i.e., channel busy state duration, channel idle state duration). Then we investigate one-vs.-all MAC protocol classification, which means to separate one MAC protocol from the other three, by using both power features and time features.

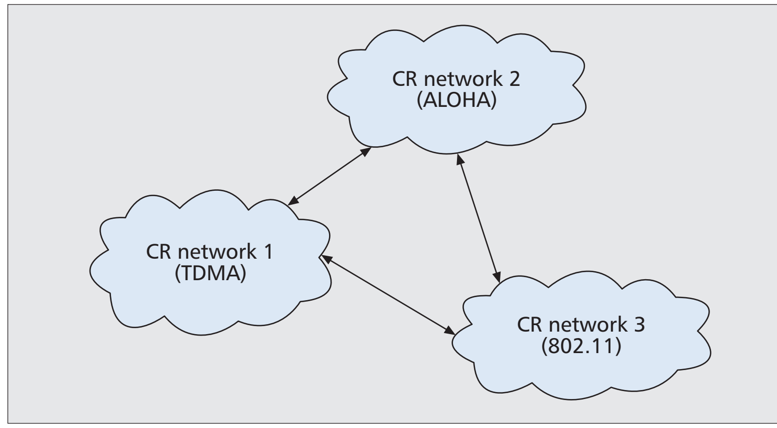

Figure 2. *Joint communication among different CR networks.*

POWER FEATURE

We consider a Rayleigh fading channel in this section; thus, the sampled instantaneous power of a packet at a given time, p_i, follows an exponential distribution with mean power p_m represented by

$$Prob(p_i) = \frac{1}{p_m} e^{-\frac{p_i}{p_m}}. \tag{7}$$

When multiple users access the channel and transmit their packets at the same time, we have the following joint probability distribution function:

$$f(p_1, p_2, \ldots p_{N_s}) = \prod_{x=1}^{N_s} \frac{1}{p_m} e^{-\frac{p_x}{p_m}} \tag{8}$$

Therefore, the sampled instantaneous power at time i, P_i, is the summation of all users transmitting their packets at the time.

$$P_i = \prod_{x=1}^{N_s} p_x \tag{9}$$

TDMA vs. Slotted ALOHA — In TDMA, a channel is divided into periodical frames in time, and each frame is further divided into time slots of equal length. The time slots are then assigned to all network users. Each user is only allowed to access the channel in its assigned time slot in each TDMA frame, which avoids contention among multiple users. In slotted ALOHA, the channel is also divided in the manner of TDMA. However, the time slots are not assigned to any specific user. Therefore, at the beginning of each time slot, the network users with packets to transmit access the channel without examining the current channel state. As a result, slotted ALOHA has the potential to lead to packet transmission collisions during each time slot, especially when the traffic load is high. Specific examples are shown in Fig. 3. In the figure, a TDMA frame is divided into 10 time slots and then assigned to 10 different network users. In this TDMA frame, we assume that seven TDMA users have packet arrivals and therefore transmit their packets in their own time slots. In slotted ALOHA, packets 1 and 2, 3 and 4, 7 and 8, and 10 and 11 are transmitted simultaneously in the first, second, seventh, and ninth time slots, respectively. As a result, the received power mean and variance of a slotted ALOHA system increase notably compared to the TDMA system, which implies that the power features of TDMA and slotted ALOHA systems have different distributions in feature space.

Pure ALOHA vs. CSMA/CA — In pure ALOHA, each user transmits its packet immediately without sensing the channel state when a packet arrives. This mechanism leads to collisions among different users when more than one user are transmitting their packets at the same time. In CSMA/CA, each user senses the channel state before beginning packet transmission. If the channel is sensed idle and stays idle for a fixed time interval, the user will then transmit its packet. If the channel is sensed busy, the corresponding user backs off and then senses the channel again. Through carrier sensing, collision is avoided; therefore, the distribution of power mean and power variance features of pure ALOHA and CSMA/CA systems are different, similar to the case of TDMA vs. slotted ALOHA.

Since the received power of each network user's packet transmission can be different because a different user has different transmission power and experiences a different channel fading scenario, the power feature is therefore extracted from the total received power (P_i in Eq. 9) instead of p_x. In a practical scenario, the network topology, channel fading scenario, and users' transmission power are fixed when a CR user captures a power sample, and the only variable is the MAC protocol type. Based on the aforementioned analysis, the P_i has a different power mean, and power variance distributions are only caused by the collisions. To illustrate the different power distributions of each network, the power mean and power variance feature spaces are shown in Fig. 4. In the figure, each network has 10 users, and the received power of a user follows an exponential distribution with mean equal to 1. To facilitate comparison, we set the network traffic load to be 0.1 and 1, respectively. The first two subfigures illustrate the power mean and power variance distribution of TDMA and slotted ALOHA protocols, and the last two subfigures illustrate the CSMA/CA and pure ALOHA protocols. From the figure, we observe that the features are mixed together when the traffic load is very low, which is mainly because CR users will hardly find a collision (power increase) in this case. As the traffic load increases, more collisions occur among users,

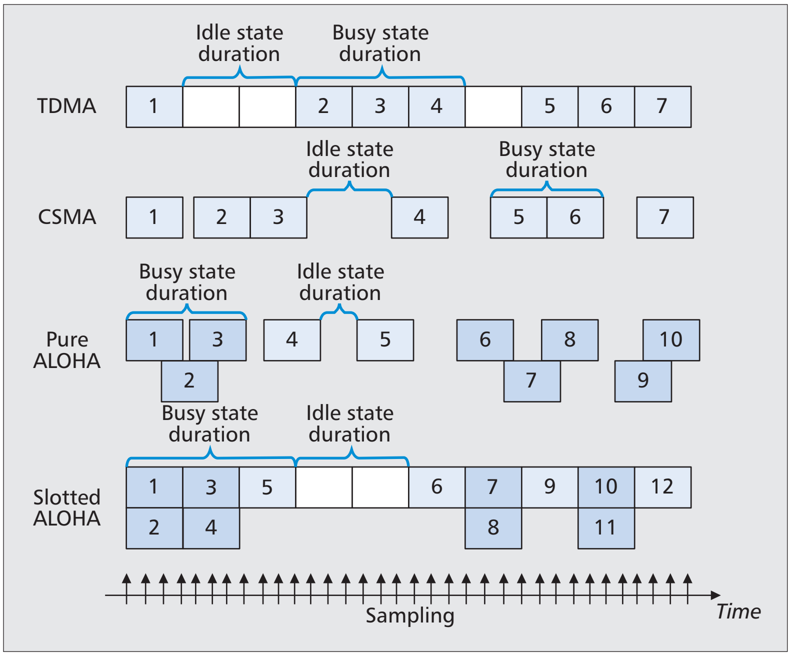

Figure 3. *MAC protocols.*

and therefore, the sampled power mean and variance increase in slotted ALOHA and pure ALOHA systems.

Time Feature

TDMA vs. Pure ALOHA — In a TDMA system, each PU accesses the channel at the beginning of its corresponding time slot in each TDMA frame and completes a packet transmission at the end of a time slot. The time length that is used for transmitting one packet, that is, one packet transmission duration (OPTD), is equal to the length of a time slot. In TDMA, the durations of channel busy state and idle state are modeled as integral times of the OPTD. In pure ALOHA, each PU accesses the channel immediately when it has packet arrivals, which is a random process in the time domain, and therefore the duration of the channel idle states is not necessarily integral times of the OPTD. Moreover, collision exists among different pure ALOHA users, and therefore the packet transmission durations overlap when the collision happens. As a result, the channel busy state duration is not always during integral times of the OPTD.

CSMA/CA vs. Slotted ALOHA — In CSMA/CA, packet transmission collisions among PUs are avoided through carrier sensing. Therefore, the duration of the channel busy states is also integral times of the OPTD. However, the duration time of the channel idle state is not necessarily integral times of the OPTD because a CSMA/CA PU starts its transmission or retransmission process randomly in time. In slotted ALOHA, multiple users only contend for the channel and start their transmissions at the beginning of each time slot and complete their transmissions at the end of each time slot. Thus, the duration of both channel busy states and idle states are still integral times of the OPTD as in TDMA.

Examples of time feature spaces are showed in Fig. 5. In the figure, the OPTD of each primary system is normalized to 1. The channel busy state duration and channel idle duration are plotted in the figure. The first two plots illustrate the time feature of TDMA and pure ALOHA networks. We observe that both plots show that TDMA features always have the integer coordinates in the feature space, but pure ALOHA features spread in the feature space. Moveover, the channel busy duration of a pure ALOHA system has a very high probability of being integer when the traffic is very low because when the traffic is low, a CR user hardly has a packet transmission collision in the pure ALOHA system. However, as the traffic increases, the packet transmission collision probability increases. As a result, the channel busy state duration features spread in the feature space. In the third and forth plots, the channel state duration features of CSMA/CA and slotted ALOHA are illustrated. In the figure, the slotted ALOHA system features also have integer channel busy and channel idle durations like a TDMA network. However, the CSMA/CA network time feature is quite different from a pure ALOHA network. In the CSMA/CA network, the channel busy duration features always have integer channel busy duration because of the collision avoidance mechanism, while the channel idle state duration features spread in the feature space.

Considerations of Both Power and Time Features

Power features and time features can be used separately to perform the one-vs.-one identification of some MAC protocol pairs, as presented above. However, considering one-vs.-all MAC protocol identification using a single type of feature is not sufficient. For example, power features have difficulties to identify TDMA and CSMA/CA because a CR user is unable to detect a packet transmission collision. Similarly, it is hard to use time features to classify TDMA and slotted ALOHA because both the channel busy state duration and channel idle state duration are integral times of the OPTD. In this article, we consider a primary network randomly using one MAC protocol among TDMA, CSMA/CA, slotted ALOHA, and pure ALOHA. Both the power features and time features are extracted by a CR user, and a four-dimensional feature space is created. A machine learning technique, SVM, is then used to identify the four MAC protocols in this feature space.

Experiment

To evaluate the MAC identification performance, we consider four MAC protocols, TDMA, CSMA/CA, pure ALOHA, and slotted ALOHA, in this article. Power features and time features are extracted from the received signal. We then use SVMs to identify the MAC protocol type of the received signal.

Feature Extraction

In the experiment, we extract power and time features from the received signals. In the feature extraction stage, each CR user keeps sensing the

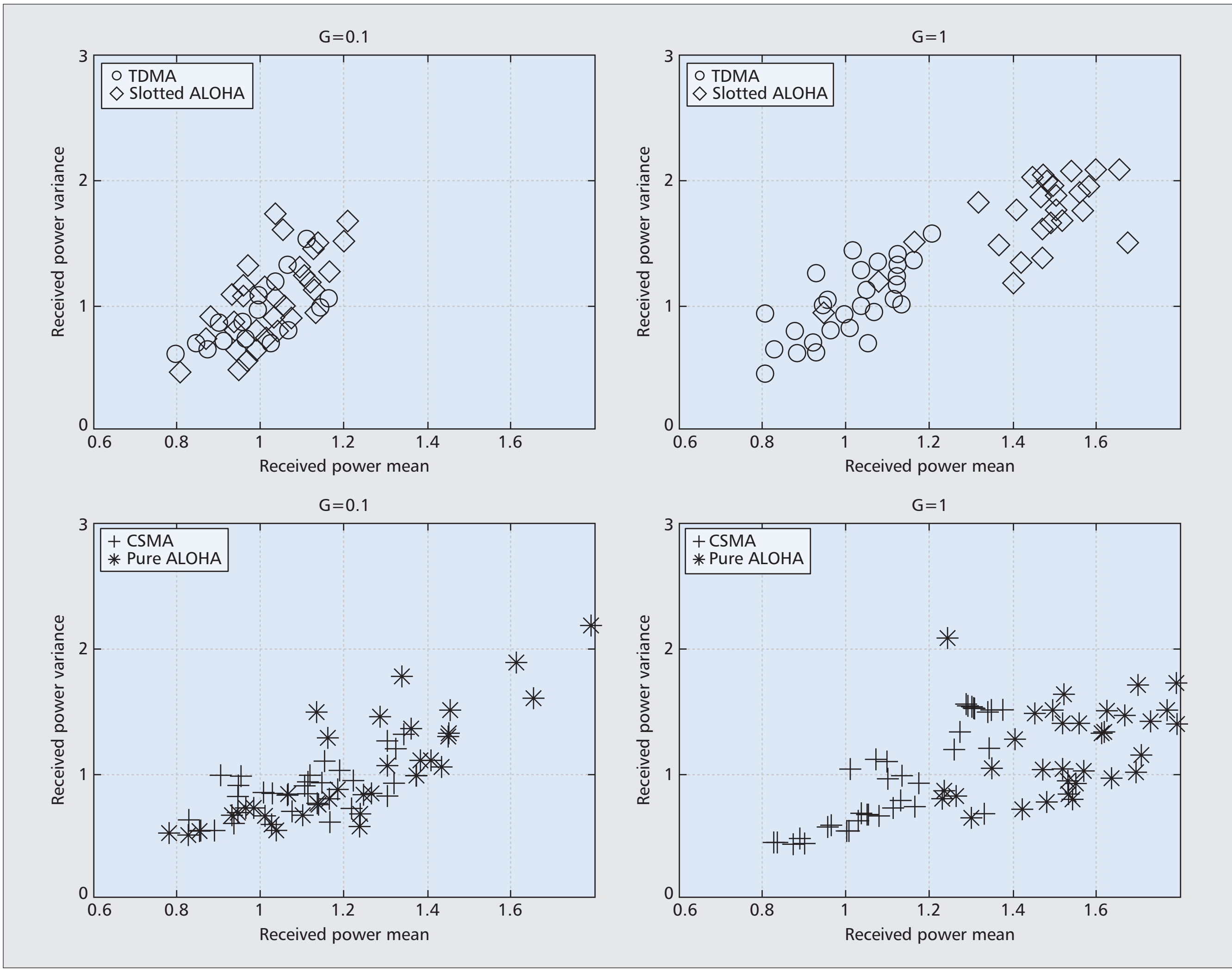

Figure 4. *Power feature space.*

channel and recording the received signal power and channel state durations, which are then used to generate the features. The feature extraction algorithm is shown in Box 1.

In the feature extraction algorithm, each CR user senses the channel at a fixed frequency and records the received power $P(n)$. Meanwhile, the CR user also checks the channel states. If the sensed channel is switched from idle to busy, the CR user will record the channel idle duration. If the sensed channel is switched from busy to idle, the CR user will then record the channel busy duration. After N power samples are gathered, the CR user begins to calculate the power mean and power variance of the recorded power samples. The calculated power mean and power variance are then used as power features. Meanwhile, the CR user will find the minimum, median, and maximum values of the recorded channel idle and channel busy durations, respectively. The six values are then used as time features for the MAC protocol identification.

Numerical Results

In our experiment, we assume that the received power of each packet is different and follows an exponential distribution with power mean 1 and variance 1. The number of network users is set to 10, and the traffic load of the network is set as 0.5 and 1.0. The buffer size of each TDMA user is set to 10. We extract 2000 feature sets for each type of MAC protocol, which means that a total of 8000 sets are used in SVMs to perform the test. In each run of the test, SVMs randomly split the 8000 samples into two groups. The first group is used to train the SVMs, and the second group is used to test the trained SVMs. Three different kernel functions, linear function, polynomial function, and radial basis function, are used in the SVMs.

The SVMs' receiver operating characteristic (ROC) curves of the experiment are shown in Figs. 6 and 7. In Fig. 6, the network traffic load equals 0.5. The linear, polynomial, and radial kernels are used by the SVMs to identify the MAC protocols, respectively. In order to show the impact of network traffic, the network traffic load is set to 1, and the same kernels are used in Fig. 7. We observe that the trained SVM using the same kernel function has different identification performance for the four MAC protocols, which is due to the fact that different MAC protocols have different characteristics; that is, S-ALOHA is much easier to identify than the

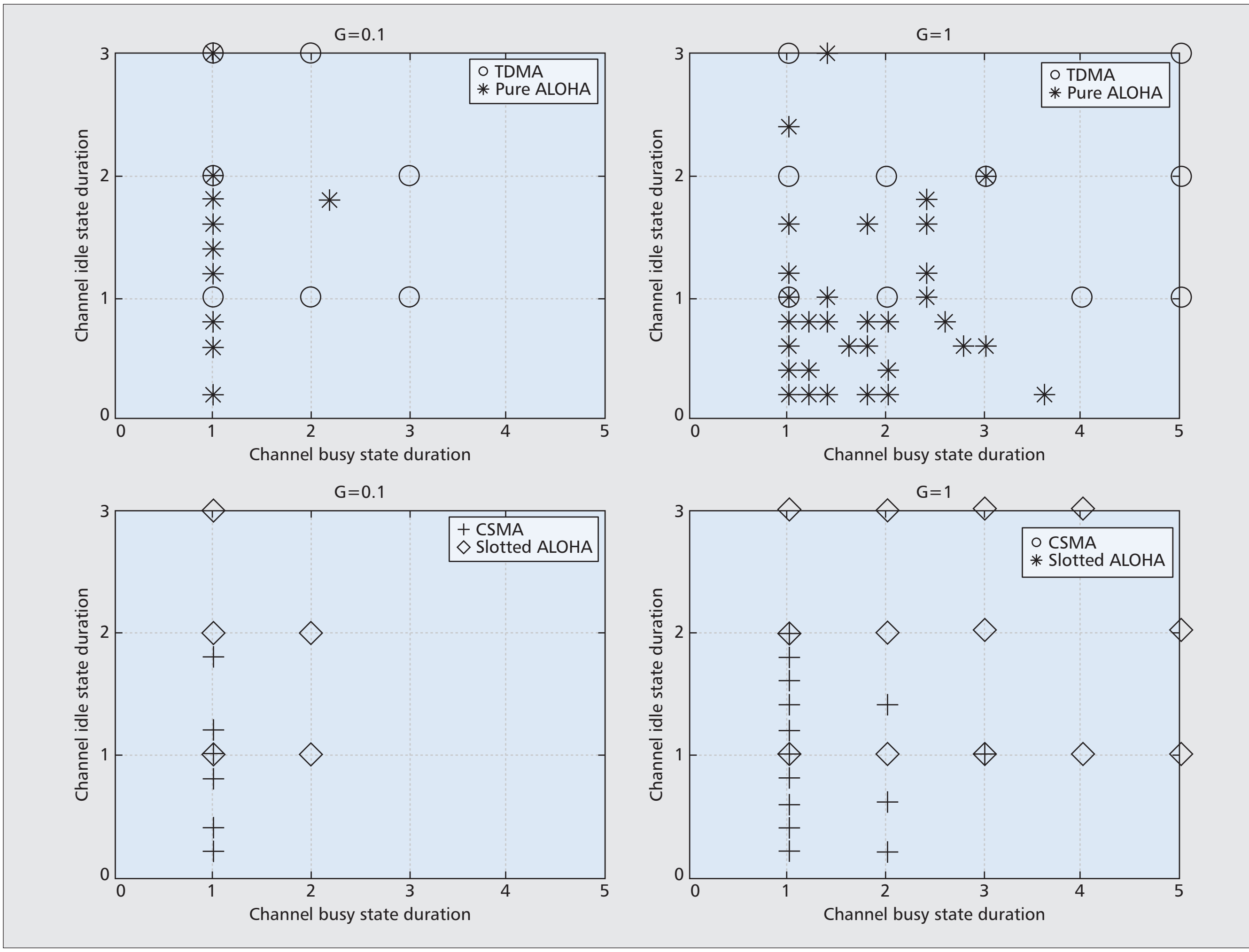

Figure 5. *Time feature space.*

1) while $n < N$
2) record the received power $P(n)$
3) if channel switched from idle to busy
4) record the channel idle duration $T_i(n)$;
5) elseif channel switched from busy to idle
6) record the channel busy duration $T_b(n)$
7) calculate the power mean P_m, and power variance P_v from the recorded N samples;
8) find the minimum, median and maximum of the recorded channel idle duration and busy duration, T_{imin}, T_{imid}, T_{imax}, T_{bmin}, T_{bmid}, T_{bmax}, respectively;
9) finalize the feature output $\{P_m, P_v, T_{imin}, T_{imid}, T_{imax}, T_{bmin}, T_{bmid}, T_{bmax}\}$;

Box 1. *Feature extraction algorithm.*

other three protocols because the high contention behavior provides more accurate power features. We also observe that different SVMs using different kernel functions have different performance on the same MAC protocol. The linear and polynomial kernels perform better than the radial base kernel in our experiment, which implies that kernel selection will be critical because it influences the identification accuracy. Moreover, considering different traffic load, we observe that the MAC protocol identification accuracies improve with the increase of the traffic load due to the fact that higher traffic load results in high packet collision probability, which will provide more information (both power information and time information) when SVMs are applied to perform the identification.

Conclusion

In this article, we introduce MAC protocol identification for cognitive radio networks. Power and time features are extracted and used by SVMs to identify the network MAC protocol types. The feature extraction algorithm is presented, and an experiment is performed. The experimental results show that MAC identification can effectively identify different MAC protocol types, which has significant potential for CR applications.

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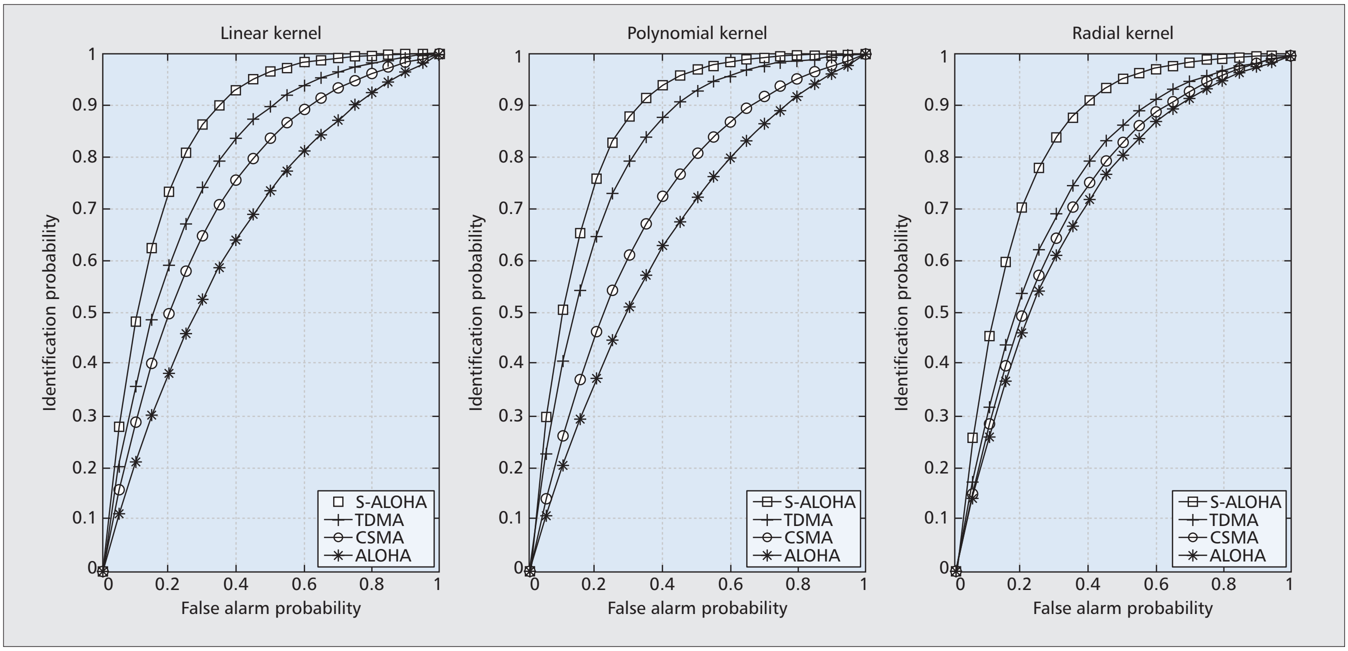

Figure 6. *ROC curve for traffic load* G = *0.5.*

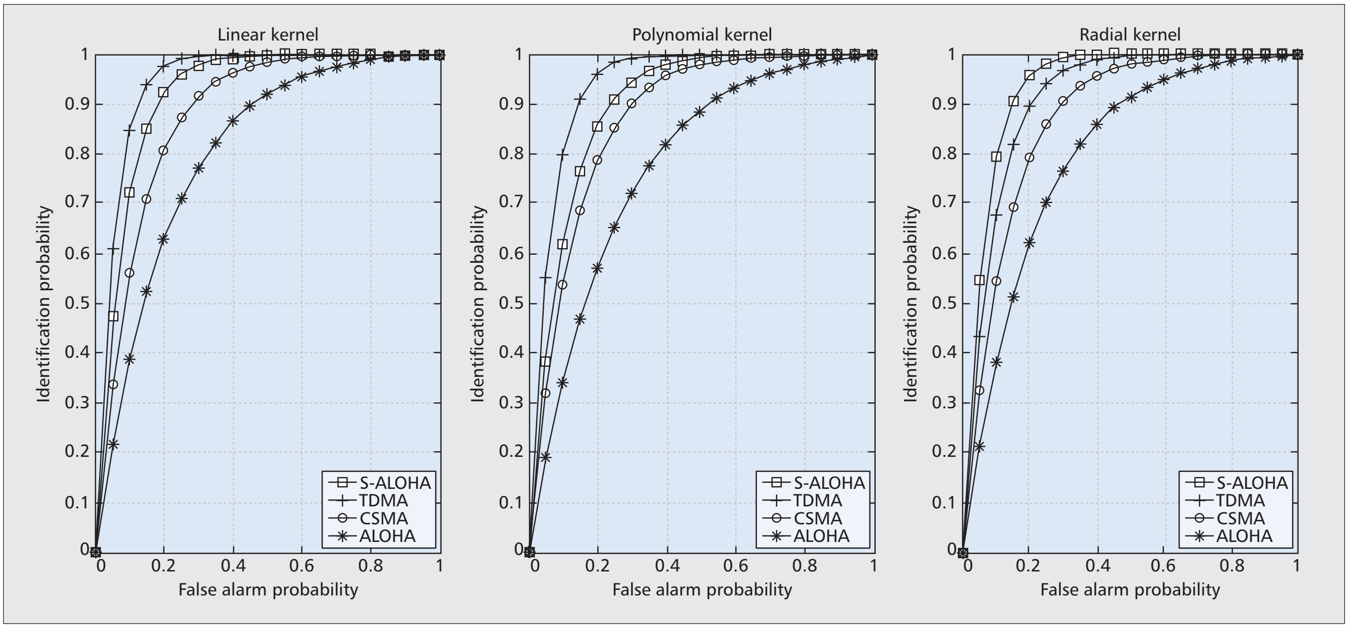

Figure 7. *ROC curve for traffic load* G = *1.0.*

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