Machine Learning-Aided Radio Scenario Recognition for Cognitive Radio Networks in Millimeter-Wave Bands

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Abstract. Radio scenario recognition is critically important to acquire comprehensive situation awareness for cognitive radio networks in the millimeter-wave bands, especially for dense small cell environment. In this paper, a generic framework of machine learning-aided radio scenario recognition scheme is proposed to acquire the environmental awareness. Particularly, an advanced back propagation neural network-based AdaBoost classification algorithm is developed to recognize various radio scenarios, in which different channel conditions such as line-of-sight (LOS), non-line-of-sight (NLOS), and obstructed line-of-sight (OLOS) are encountered by the desired signal or co-channel interference. Moreover, the advanced AdaBoost algorithm takes the offline training performance into account during the decision fusion. Simulation results show that machine learning can be exploited to recognize the complicated radio scenarios reliably and promptly.

Keywords: BP-AdaBoost · Channel condition recognition
Cognitive radio networks · Machine learning · Radio scenario recognition

1 Introduction

In light of the emerging fifth generation (5G) mobile communication systems, massive MIMO, ultra-dense networks (UDN) and millimeter-wave communications are among the most promising technologies. To deal with the challenging interference management issues of ultra-dense small cell networks operating in the millimeter-wave bands, cognitive radio (CR) technologies can to be employed [1]. CR has been investigated intensively as an effective approach to dynamically adapting to the changes of environment and quality of service (QoS) of users. In cognitive radio networks, observation, reconfiguration and learning abilities are commonly expected [1]. Comprehensive

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situation awareness, especially, the radio scenario recognition, is the prerequisite to acquiring or enhancing the learning ability of CR. A radio scenario can be characterized by a broad range of features in context of network topology, locations and configurations of base stations (BS) and user equipment (UE), radio propagation condition, spectrum usage, and source of interference, just to name a few. Moreover, in order to meet with the varying QoS requirements of UEs in the dense small cell environment, comprehensive situation awareness is required as the power of both desired signal and co-channel interference could be dynamically changing. For future ultra-dense small cell networks operating in the millimeter-wave bands, the ability of radio scenario recognition and interference management becomes even more important in order to identify the actual source of co-channel interference and the channel condition for the desired signal as well as the co-channel interference. Only with accurate and prompt radio scenario awareness, the QoS of users can be better ensured by making appropriate adaptations or reconfigurations of radio parameters. Mobility support and QoS support for millimeter-wave wireless networks are the major motivations for this work. How to realize comprehensive radio scenario recognition for ultra-dense networks in the millimeter-wave bands is the main issue investigated in this paper.

As we know, machine learning is an effective approach to voice or image recognition. Some research on machine learning-based scenario recognition focuses on robotics or image processing by employing probabilistic models, convolutional neural networks or multi-layered neural networks [2–4]. For the radio environmental awareness, radio scenario recognition may include various aspects such as spectrum occupation, signal classification, and radio channel condition recognition [5–9]. For example, a spectrum prediction algorithm based on artificial neural networks is proposed in [5]; spectral coherence and artificial neural networks are further employed to classify the modulation types of signals [6]. With regard to the channel condition, some researchers analyze the statistical characteristics of the received signal [7], while some researchers apply machine learning algorithms to none-LOS (NLOS) identification for ultra-wide band (UWB) systems [8, 9]. For example, a NLOS identification algorithm based on least square support vector machine (LSSVM) is presented in [8]. However, in order to improve the positioning accuracy, most of the existing work on radio channel condition recognition mainly considers the classification of line-of-sight (LOS) and none-LOS (NLOS) for the desired signal only. Communications in the millimeter-wave bands need to consider more environmental factors such as obstruction due to foliage. Scenarios with the obstructed LOS (OLOS), which are caused by moving or fixed objects (e.g., pedestrians, trees), are usually ignored for communications in low-frequency bands (e.g., sub-6 GHz band). Moreover, in order to improve the classification ability, boosting algorithms have been adopted to develop a strong classifier by combining multiple "weak" classifiers or base classifiers [10]. The weak classifier can be based on back propagation neural network (BP-NN) or support vector machine (SVM). AdaBoost algorithm is a kind of boosting algorithms. The AdaBoost algorithm enables high accuracy of classification with simple structure, which is suitable for the nonlinear classification problems of radio scenario recognition. In addition, radio environmental map (REM) which stores multi-dimensional radio scenario parameters has been proposed for CRs [11]. REM can serve as the "navigator" for the CRs by offering very comprehensive radio scenario information.

This article proposes a generic machine learning-aided radio scenario recognition scheme for dense small cell networks operating in the millimeter-wave bands. An advanced back propagation neural network based AdaBoost (BP-AdaBoost) algorithm is developed, which takes the offline training performance into account during the decision fusion. To the best of our knowledge, it is the first attempt to employ the AdaBoost algorithm for radio scenario recognition. Furthermore, three kinds of channel conditions (namely, LOS, NLOS, and OLOS) are taken into account for both the desired signal and the co-channel interference. Simulation results demonstrate the effectiveness and the advantages of the proposed algorithm.

The rest of this paper is organized as follows. In Sect. 2, the framework of machine learning-aided radio scenario recognition scheme is proposed. Main modules of radio scenario recognition are discussed in details. In Sect. 3, the advanced BP-AdaBoost algorithm is analyzed. In Sect. 4, the simulation results are presented to show the key performances. Summary is given in the last section together with discussions on future work.

2 Framework of Radio Scenario Recognition

Figure 1 shows the framework of the proposed radio scenario recognition scheme, which mainly consists of the following four key modules.

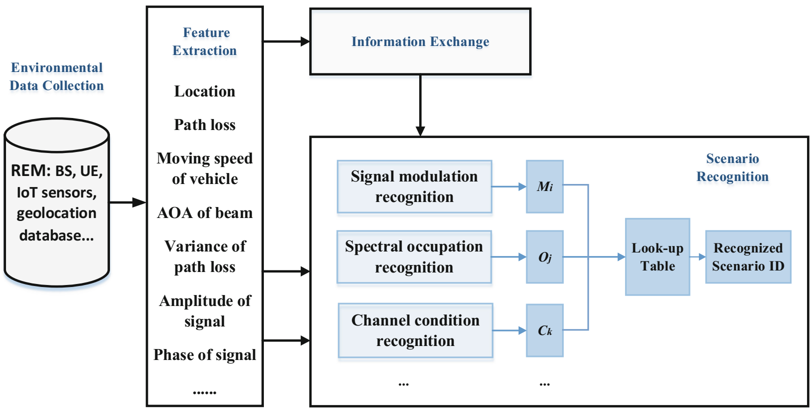

Fig. 1. Framework of the proposed radio scenario recognition scheme.

(i) **Environmental data collection** module: this module collects environmental data from multiple sources such as BS, UE, geolocation database, various environmental sensors, e.g., rain fall meter, Internet of things (IoT) sensors and the REM [11, 14].

(ii) **Feature extraction** module: this module extracts the useful features such as the path loss and its statistics, angle-of-arrival (AoA) of the desired signal and interference. Furthermore, instantaneous amplitude, phase and frequency of the signal can be employed for modulation classification or recognition.

(iii) **Information exchange** module: this module exchanges the system information among different entities such as BS, UE, and spectrum coordinator to make informed decisions, e.g., to classify the source of co-channel interference (either intra-cell interference or inter-cell interference).

(iv) **Scenario recognition** module: this module conducts the classification tasks relevant to scenario recognition, such as channel condition recognition, signal modulation recognition, spectral occupation recognition, and so on. The radio scenario type (i.e., the scenario ID in Fig. 1) can be determined by retrieving a look-up table, which maps the results of various recognition tasks such as channel condition, signal modulation, and spectral occupation. Each recognized scenario ID represents a unique radio scenario of interest.

This article takes the channel condition recognition as an example in the following subsections. To obtain comprehensive channel condition recognition in the millimeter-wave bands, not only LOS/NLOS but also OLOS are considered for both the desired signal and the co-channel interference. Figure 2 shows four typical radio scenarios with different channel conditions, just for illustration. Among these scenarios, Fig. 2(a) and (b) illustrate two scenarios with intra-cell co-channel interference, whereas Fig. 2(c) and (d) illustrate two scenarios with inter-cell co-channel interference. Particularly, in Fig. 2(a), the desired signal for UE_1 has LOS path. However, the desired signal for UE_1 is blocked by buildings and is in NLOS condition in Fig. 2(b). In Fig. 2(c), UE_1 experiences the inter-cell co-channel interference with LOS path, whereas it experiences the inter-cell interference with OLOS path in Fig. 2(d).

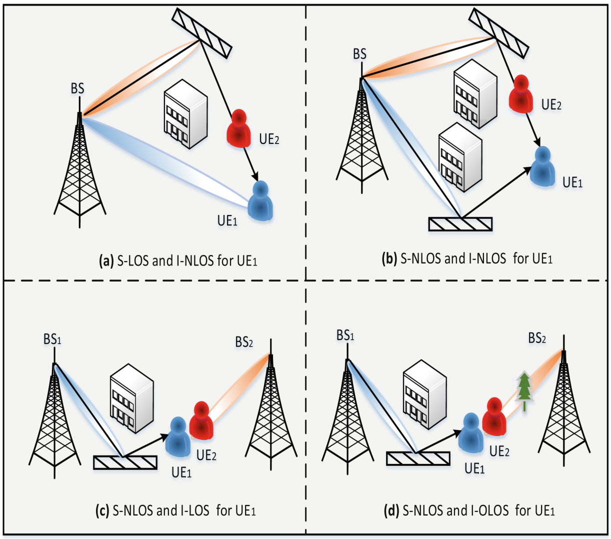

Fig. 2. Various radio scenarios of channel condition in millimeter wave bands. Note: in this figure, "S-LOS" represents the desired signal in LOS condition whereas "I-NLOS" represents the co-channel interference in NLOS condition.

2.1 Feature Extraction

To recognize the complicated radio scenario, the following parameters or features can be used for information exchange and channel condition classification.

(1) Location of UEs and BSs;
(2) AOA of the desired signal or interference;
(3) Path loss of the desired signal or the statistics of the path loss (such as variance of path loss);
(4) Root mean square delay spread;
(5) Probability distribution function of the received desired signal or interference.

As mentioned above, these features are mainly employed for information exchange and channel condition recognition. Obviously, which features are extracted and exploited can directly affect the ability and performance of radio scenario recognition. When the current features cannot meet the performance requirements, it indicates more features or deeper features from the raw data need to be extracted. For example, higher-order statistics (e.g., variance of path loss) is one of the deeper features employed in this paper. Similarly, the key idea of deep learning (e.g., convolutional neural networks and deep belief networks) is to design a feature extractor which transforms the raw data into a suitable internal representation [12]. The performance of radio scenario recognition can be enhanced by exploiting the additional deeper features.

2.2 Information Exchange

Interference exchange module is a critically important module in the proposed radio scenario recognition framework, especially for dense small cell networks. With exchanged information from neighboring cells, the source of interference and the type of co-channel interference can be determined effectively. The flow chart of information exchange between network entities such as UE, serving BS and spectrum coordinator (SC) is elaborated in Fig. 3. The key procedures are discussed as follows.

(1) UE transfers “information-1” to the serving BS (①). Note: “information-1” in Fig. 3 refers to the UE location information, received power, AOA, etc.
(2) According to the extracted features, the serving BS checks whether co-channel interference exist or not (by evaluating the interference-to-noise ratio of UE). If co-channel interference exists, the BS further checks whether the co-channel interference is from the serving cell itself (②–③).
(3) If it is determined that the co-channel interference is from the neighboring cell, the serving SC will find out which BS is the source of co-channel inter-cell interference first, and then report to the serving BS (④–⑤). Note: “information-2” in Fig. 3 includes the information about the source of interference.
(4) Based on the collected data and the exchanged information, the serving BS recognizes the type of interference (⑥).

With the help of the information exchange module, the various channel conditions of the desired signal as well as the various types of co-channel interference are taken into account in the scenario recognition module.

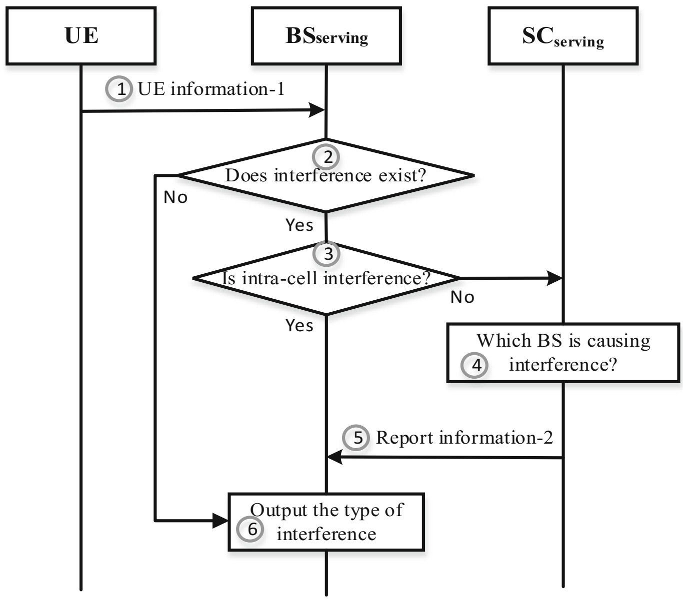

Fig. 3. Information exchange for co-channel interference recognition. Note: "information-1" refers to the UE location information, received power, AOA, etc.; "information-2" refers to the source of interference.

3 Advanced BP-AdaBoost Algorithm

In this section, the proposed advanced BP-AdaBoost algorithm for the radio scenario recognition module is discussed in two subsections. In the first subsection, the traditional BP-AdaBoost algorithm is discussed, which is a matured approach to simple classification problems with two different classes. The most convenient way is to apply the AdaBoost algorithm to multi-class problems directly. In the second subsection, the proposed advanced BP-AdaBoost algorithm can be used to address more complicated classification problems with multiple classes through decision fusion. Channel condition (e.g., LOS, NLOS, and OLOS) classification is an example application of the radio scenario recognition.

3.1 BP-AdaBoost Algorithm

Back propagation neural network (BP-NN) is well-known for its pattern recognition or classification capability. In this paper, BP-NN is employed as the "weak classifier" or "sub-classifier" of the AdaBoost algorithm. The BP-AdaBoost algorithm employs a number of BP neural networks in a cascade structure.

The BP-AdaBoost algorithm is carried out according to the following steps, as shown in Fig. 4.

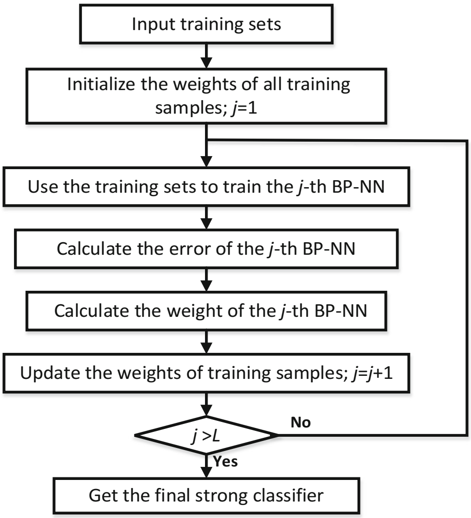

Fig. 4. Block diagram of the BP-AdaBoost algorithm

(1) Input the training sets: (x_i, y_i), $i = 1, 2, \ldots, K$; x can be a matrix populated with the selected features; y_i = 1 or −1, where "1" and "−1" represent the two types of scenarios to be recognized, respectively.

(2) Initialize the weights of all training sets, and set j = 1.

$$D_j(i) = \frac{1}{k}. \tag{1}$$

(3) Use the training subset (x_i, y_i) for training the j-th BP-NN and then get the output $g_j(i)$ of the BP-NN sub-classifier in the training step.

(4) Calculate the error (ε) of the j-th BP-NN as defined by (2).

$$\varepsilon = \sum_{i=1}^{K} D_j(i)\left(\frac{|g_j(i) - y_j(i)|}{2}\right). \tag{2}$$

(5) Calculate the weight (α_j) of the j-th BP-NN as expressed by (3).

$$\alpha_j = \frac{1}{2}\ln\left(\frac{1-\varepsilon}{\varepsilon}\right). \tag{3}$$

(6) Update the weights of training samples by (4) and (5).

$$D_{j+1}(i) = D_j(i)\exp(-\alpha_j g_j y_j). \tag{4}$$

$$D_{j+1}(i) = \frac{D_{j+1}(i)}{B_j}. \tag{5}$$

where B_j is a normalization factor to ensure that the sum of the weights is equal to 1. B_j is defined by (6).

$$B_j = \sum_{i=1}^{K} D_{j+1}(i). \tag{6}$$

(7) Increase j by 1, i.e., $j = j + 1$. If $j > L$ (where L is the total number of BP neural networks employed by the BP-AdaBoost algorithm), get the final strong classifier $Y(x)$ as defined by (7). Otherwise, repeat Step-3.

$$Y(x) = sign\left[\sum_{j=1}^{L} \alpha_j g_j\right]. \tag{7}$$

Note that, as indicated by (7) in the last step of the BP-AdaBoost algorithm, the output of the strong classifier only has two types of output, i.e., either 1 or −1. The BP-AdaBoost algorithm used in the article can be replaced by any other classifiers which can distinguish two classes (e.g., Bayes classifier, LSSVM, etc.).

3.2 Advanced BP-AdaBoost Algorithm

Figure 5 shows the block diagram of the proposed advanced BP-AdaBoost classification algorithm, which employs a number of BP-AdaBoost sub-classifiers in parallel. To make more reliable radio scenario recognition, both the offline training performance for each scenario and the online classification results from each sub-classifier are taken into account during the decision fusion.

Supposing there are M ($M \geq 3$) different types of radio scenarios to be recognized, N sub-classifiers need to be employed and N is defined by (8).

$$N = C_M^2. \tag{8}$$

where C_M^2 is the total combinatorial number for taking any two types of scenarios out of M different scenarios.

Accordingly, N input data sets are collected and each input data set consists of the training or testing data corresponding to two different types of scenarios, as shown in the top box of Fig. 5. Note that each input data set may include a number of features. The detailed procedure of the advanced BP-AdaBoost algorithm is discussed as follows.

(1) The first step is to initialize the input data sets. The data sets include training sets and testing sets tagged by M different types of scenarios. For instance, "data set-i" consists of training data and testing data sets corresponding to "scenario-i".

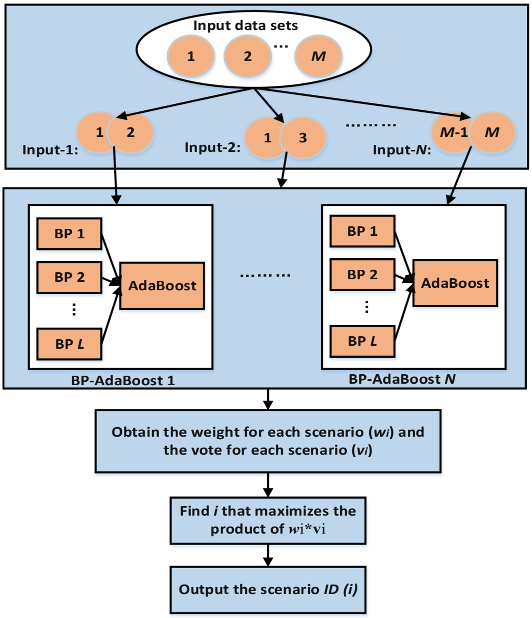

Fig. 5. Block diagram of the advanced BP-AdaBoost classification algorithm

(2) The second step is to train and test the BP-AdaBoost neural networks. The input set-j corresponds to the input of j-th BP-AdaBoost sub-classifiers, which can identify two different types of scenarios.

(3) The third step is to calculate the vote of N BP-AdaBoost classifiers for each scenario and the weight for each scenario. For instance, the vote (v_i) represents the total number of votes for the i-th scenario by N sub-classifiers; The weight (w_i) represents the average correct recognition rate for the i-th scenario in the training stage. In the testing stage, j-th sub-classifier outputs the recognized "scenario ID", say, i. In some sense, the weight (w_i) shows the offline training performance for the i-th scenario, as defined by (9).

$$w_i = \frac{\sum_{j=1}^{N} R(i,j)}{M-1}. \tag{9}$$

where, $R(i, j)$ is the correct recognition rate corresponding to the i-th scenario for the j-th BP-AdaBoost sub-classifier.

(4) The fourth step is to make decision fusion for each scenario through a weighted voting. The product of weight (w_i) and vote (v_i) for each scenario is calculated and then find out the scenario ID (i) which corresponds to the maximal product, as expressed by (10).

$$\max_{i} w_i v_i \quad i = 1, 2, \ldots, M. \tag{10}$$

(5) The final step is to output the recognized scenario ID (i).

The channel condition recognition module is an example application of the advanced BP-AdaBoost algorithm. In this example, to recognize the LOS, NLOS, or OLOS scenario, the total number of channel conditions to be recognized is 3.

4 Simulation Results

Simulations are conducted to evaluate the performance of the proposed advanced BP-AdaBoost algorithm. The simulation results demonstrate the effectiveness of the advanced BP-AdaBoost algorithm. Taking the channel condition recognition as an example, the simulated scenarios include LOS, NLOS and OLOS. The system settings and key parameters assumed in the simulations are listed in Table 1.

Table 1. System parameters used in the simulation

Parameters	Value
Operating frequency	28 GHz
Number of hidden layer	1
Number of hidden layer nodes	6
Number of iterations in BP neural network	5
Learning rate of BP neural network	0.1
Learning goal of BP neural network (i.e., recognition error rate)	0.0004
Number of BP neural networks in AdaBoost (L)	10
Number of scenarios to be recognized (M)	3
Number of training sets or samples (K)	10000
Number of testing sets or samples	1000
Path loss exponent of OLOS/NLOS/LOS (α)	2.5/3.4/2.1
Shadow factor of OLOS/NLOS/LOS (σ in dB)	5.5/9.7/3.6

Moreover, the simulation is carried out by using the following millimeter-wave path loss model [13], as defined by (11).

$$PL[dB](d) = 20 \times \log_{10}\left(\frac{4\pi d_0}{\lambda}\right) + 10\alpha \log_{10}\left(\frac{d}{d_0}\right) + X_\sigma. \tag{11}$$

where d_0 is the given reference free space distance (d_0 = 1 m); λ is the wavelength of the carrier frequency (28 GHz); d is the distance between the transmitter and the receiver in meters ($d \geq d_0$); X_σ is a random variable following the zero mean Gaussian distribution of $N(0, \sigma^2)$; α is the path loss exponent and σ is the shadow factor.

Figure 6 shows the performance comparison of the advanced BP-AdaBoost algorithm when using single feature vs. two features. Note that in Fig. 6, “Single feature” represents the “path loss” only whereas “Two features” refers to “path loss” and “variance of path loss”. Figure 6 shows the correct recognition rate trained by two features is higher than that when trained by single feature, especially for the OLOS recognition. In addition, for all three types of channel conditions, the correct recognition rates are over 99% when using two features. The simulation results indicate that an internal representation of raw features (e.g., the variance of path loss) can improve the performance of classifier significantly and reveal the potential benefits of exploiting the deeper features.

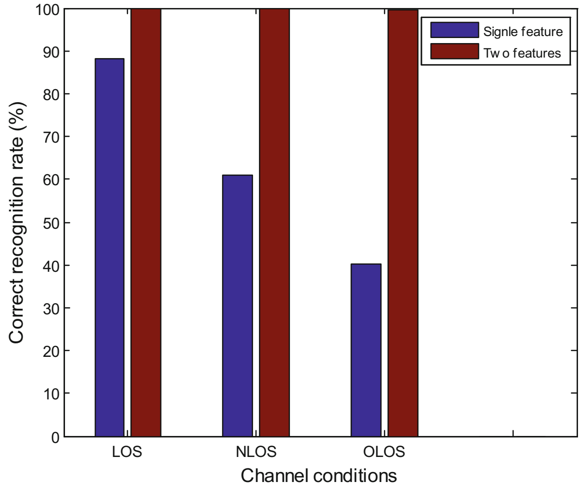

Fig. 6. Performance of the advanced BP-AdaBoost in terms of correct recognition rate

Furthermore, we compare the performance of the advanced BP-AdBoost algorithm with the traditional LSSVM algorithm in terms of correct recognition rate and operation time, as shown in Table 2 and Fig. 7. The correct recognition rate for LOS and NLOS are obtained with the same training and testing sets. The algorithm with two features has good ability to identify different types of channel conditions, which is shown in Table 2.

Table 2. Comparison of correct recognition rate

Methods	Correct recognition rate			
	LOS		NLOS	
	Two features	Single feature	Two features	Single feature
Advanced BP-AdaBoost algorithm	99.9%	88.3%	100%	60.9%
LSSVM [8]	99.8%	74.4%	100%	60.3%

Figure 7 shows the comparison of operation time (i.e., the computer running time) with different number of training samples (K = 6000 and 7000, respectively). Note that the simulation is conducted with a laptop computer (CPU: intel core i7 quard core, 2 GHz clock rate, and 4 GB RAM). With the increase of training samples, the operation time of the proposed Advanced BP-AdaBoost algorithm increases slightly whereas the LSSVM classifier requires much longer operation time. This simulation result shows that the proposed algorithm can ensure the effectiveness of scenario recognition and has faster training speed than the LSSVM algorithm. This simulation result also indicates the computational complexity of the proposed algorithm is much lower than the LSSVM.

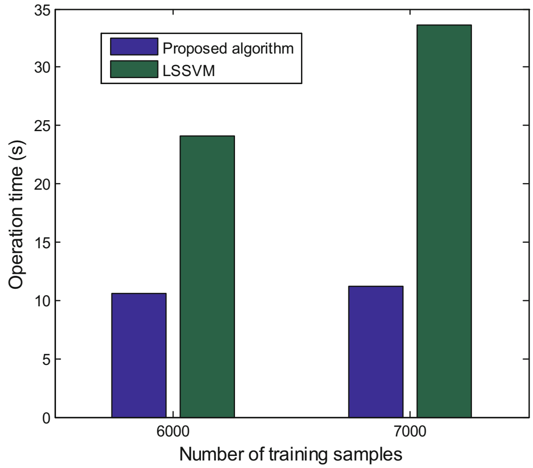

Fig. 7. Operation time comparison between the advanced BP-AdaBoost and LSSVM.

In sum, the simulation results demonstrate that the radio scenario recognition based on our proposed advanced BP-AdaBoost algorithm has significant performance advantages in terms of correct recognition rate and computational complexity. The advantages of the proposed scheme will become even more pronounced when dealing with more complicated scenarios such as scenarios with multiple interferers. Specifically, with the help of comprehensive environmental data obtained from multiple sources, it is highly possible to recognize the channel condition of each interferer separately by taking advantage of the narrow beamwidth of millimeter-wave antennas.

5 Summary

To obtain comprehensive and prompt radio scenario cognition for cognitive dense small cell networks operating in the millimeter-wave bands, a generic framework of machine learning-aided radio scenario recognition scheme is proposed in this paper. Particularly, taking the channel condition recognition as an example application, an advanced BP-AdaBoost algorithm is developed to identify the LOS, NLOS or OLOS channel conditions for both the desired signal and the various types of co-channel interference. Decision fusion is employed in the advanced BP-Adaboost algorithm, which takes the offline training performance into account. The correct recognition rate and operation time of the advanced BP-AdaBoost algorithm are evaluated and compared against the traditional LSSVM algorithm through simulations, which demonstrates the significant advantages of the proposed algorithm. Simulation results also indicate additional features or deeper features can help to improve the performance of the radio scenario recognition.

The scenario classifier simulated in this paper takes a simplistic view of the types of "scenarios", seeking predominantly to classify the signal path of interest and a single interference path as LOS, NLOS, or OLOS. For future work, we may consider more complicated scenarios with multiple interferers. The complexity of the proposed advanced BP-AdaBoost algorithm can be further analyzed and optimized. In addition, the operation time of the advanced BP-AdaBoost classifier might be further reduced by adopting parallel programming with multi-core CPU or graphics processing unit (GPU). Moreover, the internal functions of the AdaBoost algorithm can be further studied to export multiple classes directly. Last but not least, thorough performance evaluation with real-world measurement data is another important task of future work.

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