Wireless Network Optimization Method based on Cognitive Cycle using Machine Learning

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Abstract: The wide spread of mobile communication devices has increased the opportunities to use wireless communication technologies, irrespective of one’s geographical location. However communication quality deteriorates due to factors such as competition for scarce radio resources and interference among nearby devices. Cognitive radio technologies have been developed recently to conquer such difficulties. In this paper, we propose a wireless network optimization method using learning algorithms based on a control model known as cognitive cycle. We implement the proposed optimization method in wireless LANs and evaluate the throughput performance. The experimental results show the effectiveness of the proposed approach in a real environment.

Keywords: Cognitive Radio, Wireless LAN, Machine Learning, Optimization

Classification: Wireless communication technologies

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1 Introduction

Recently, wireless traffic and the number of wireless communication devices has been increasing rapidly. However, the frequency bands suitable for current technologies have already been exploited; thus, the resource is limited. Moreover, the radio environment becomes more unpredictable because of two reasons. Firstly, not only the volume but also the type of traffic is increasing, making the usage of the radio resource more complex. Secondly, distributed wireless networks such as IEEE 802.11 wireless local area networks (WLANs) are widely deployed, and the inner-system and inter-system interactions cannot be predicted easily.

Cognitive radio technologies [1, 2] have recently been developed to improve the radio resource usage of wireless networks under such situations. The basic concept of cognitive radio technology, known as cognitive cycle illustrated in Fig. 1 (a), is the adaptation of the behavior of wireless systems through the recognition and learning of the radio environment. Cognitive radio systems observe and recognize the wireless network environment, make reconfiguration decisions, and apply the corresponding action to reconfigure the network. Using this approach, various types of radio parameters can be optimized through appropriate actions. Learning the relationship between the actions and performance is achieved by increasing the number of samples. It improves the precision of the decision making for the best performance.

IEEE Std. 1900.4 [3] defines the basic architecture of such a cognitive radio system. The mobile terminals select the best radio resource to optimize the efficiency of radio resource usage. In order to make an optimal decision, the necessary information can be collected to the network reconfiguration manager. Authors have analyzed the performance optimization of such wireless networks [4]. In [5], the authors introduced machine learning in mobile terminals in order to optimize the aggregation method for IEEE
2 The concept of the proposed cognitive radio system

A number of literatures indicate that machine learning can improve the performance of wireless networks [6]. In [7], it was shown that a neural network-based channel selection in IEEE 802.11 WLAN access points (APs) can enhance the throughput in an experimental testbed. This approach is very interesting though it only considers each AP independently.

Our proposed method is, in contrast, designed to optimize all mobile terminals (MTs) in the system. Fig. 1 (b) shows the concept of the proposed method. Mobile terminals obtain the status and performance of the radio environment, then build the performance model using machine learning which represents the relationship between wireless parameters and the throughput. The information regarding the throughput model is sent to the cognitive controller via access points. The cognitive controller serves as the network reconfiguration manager. It decides the optimal set of wireless parameters for all MTs, and provides these to the MTs via the access points. Mobile terminals receive the wireless parameters and reconfigure their settings.

By repeating the above cycle, MTs accumulate information about the wireless network status and performance. The more training data is collected,
the more accurate the throughput model built, resulting in better network performance.

3 Learning and optimization

In order for cognitive radio systems to choose the best wireless parameter values for the current wireless network status, we propose a parameter estimation method using a machine learning algorithm. As shown in Fig. 1 (b), the learning algorithm builds the estimation model \( y = f(x) \) from the training samples. This model estimates the throughput \( y \) from the input parameters \( x \). In our proposed method, the training samples are the sets of measured quality of the radio environment (\( z \)), the parameters of the MTs (\( p \)), and the measured throughput \( y \). The learning algorithm estimates the relationship between \( y \) and (\( p \) and \( z \)), represented as \( y = f(p, z) \).

3.1 Parameter optimization method using machine learning

We use support vector regression (SVR) as a learning algorithm, similar to the previous research in [5]. The SVR is an analog output version of support vector machines (SVMs) [8]. In SVR, the estimation function \( f \) can be expressed as follows [9]

\[
f(x) = \sum_{i=1}^{l}(\alpha_i' - \alpha_i)K(x, x_i) + b, \tag{1}
\]

where \( l \) is the number of training samples, \( x_i \) is the input of the training samples (\( p \) and \( z \)), \( x \) is an unknown input set for the learning algorithm, and \( K \) is a kernel function, respectively. \( \alpha_i \), \( \alpha_i' \), and \( b \) are unknown parameters which are obtained by the optimization technique proposed in [9], using training samples \( p \), \( z \) and \( y \).

3.2 Optimization of wireless parameters

In order to decide the optimal set of wireless parameters \( p^* \) for the MTs, the cognitive controller solves following optimization problem

\[
\arg \max_p \sum_{n=1}^{N} \log(1 + f(p_n, z_n)), \tag{2}
\]

where \( N \) is the number of MTs, \( p_n \) is the possible parameter set for MT-\( n \), \( z_n \) is the current measured quality of the radio environment at MT-\( n \), and \( f(p_n, z_n) \) is the estimated throughput of MT-\( n \) obtained using the throughput model described above. Here, we use the logarithmic utility function of throughput considering fairness among MTs. In this formulation, MTs with lower throughputs have relatively larger gains for the objective function than those with higher throughputs.

4 Experiment and results

We implemented the proposed method in IEEE 802.11 WLAN devices. Experiments with these devices are coordinated in our university laboratory working space.
4.1 Implementation model
IEEE 802.11 WLAN APs and stations (STAs) are operated in infrastructure mode in the 2.4 GHz ISM band. Laptop PCs with Ubuntu 14.04 are used as both STAs and APs. In each cognitive cycle, the STA observes the delay and the packet loss ratio through pinging, the received signal strength indicator (RSSI) from its connecting AP using the iwconfig command, the number of packets around the STA using tcpdump command as the link quality \((z)\), and the throughput \((y)\) using the TCP iPerf command. The STA sets the transmission power, channel number (from 1 to 13), and data rate at the physical layer (from 6 to 54 Mb/s) for the current wireless parameters \((p)\).

The STA then builds the throughput model through SVR, and sends information regarding the SVR model to its connecting AP. The AP sends it to the cognitive controller. We have setup one of the APs as the cognitive controller. The cognitive controller calculates the optimal set of STA parameters \(p^*\), returns the result to the AP, then the STA gets the result from its connecting AP. In this paper we use particle swarm optimization (PSO) algorithm [10] at the cognitive controller to reduce the calculation costs for solving the optimization problem shown in Eq. (2).

4.2 Settings and results
In the experiment, three APs and nine STAs are operated in channel 1, 6, and 11 in IEEE 802.11g as shown in Fig. 2 (a). The operating channel is fixed for each AP. The locations of all APs and STAs are fixed during the experiment. We use uplink TCP throughputs to evaluate the performance since in general uplink traffic makes radio resource usage more competitive in CSMA/CA (note that the number of STAs are larger than that of APs). We also add background UDP traffic of approximately 8 Mb/s on channel 11. To verify the performance of the proposed system, the uplink throughput performance is compared with other algorithms, focusing on the selection of the connecting AP at the STA as follows: (A) selection by RSSI, (B) random selection, (C) selection by radio resource utilization, and (D) to select the number of STAs as equally as possible among channels. In algorithm (A) using RSSI, the STA selects an AP with the highest RSSI. This seems to be the popular method for devices in the market. In algorithm (C), the STA selects the AP of a channel where the minimum number of packets is observed in each cycle. In each algorithm, each cycle runs for 30 s. All STAs start iPerf traffic of 2 s at the same time in every cycle. Before starting the proposed method, the STA observes the radio environment in each channel for 1 h and utilizes this as training data.

Fig. 2 (b) shows the moving average throughput by time for each algorithm. The time is expressed as the number of cognitive cycle. The throughput is averaged every 10 cycles (5 min). The proposed method shows greater throughput than other algorithms, indicating that the STAs can select APs effectively.

Fig. 2 (c) compares the average throughput per channel among algorithms. Compared to the basic RSSI based algorithm (A), utilization based
algorithm (C) shows much higher throughput at channel 6, where it detected as most vacant channel. However, the throughputs at the other channels are much lower. This algorithm is based on the observations of wireless environment but it does not learn, nor optimize the whole system.

In contrast, the proposed method which has a function of learning and optimization shows higher throughput at channel 1 and 6, and lower throughput at channel 11 which has higher background traffic. As a whole, the proposed method can improve network performance. These results indicate that the proposed method can build the appropriate throughput model through learning, and can select the optimized wireless parameters that improves the whole network performance.

5 Conclusion

Wireless communication qualities deteriorate owing to the widespread of mobile devices and limited radio resources. Cognitive radio technologies have been developed to resolve such difficulties. In this paper, we proposed a wireless network optimization method using machine learning algorithm based on the cognitive cycle. We implemented the proposed optimization method in wireless LANs and evaluated the throughput performance. Experimental results showed the effectiveness of the proposed approach in a real environment.

Acknowledgments

This work was supported by JSPS KAKENHI Grant Number JP17K00136. The authors wish to thank Masaki Sato for his effort [11] to build the basic platform for the proposed method.