MAC Protocol Adaptation Method in Coordination with Application

Koshiro Aruga and Takeo Fujii
Advanced Wireless and Communication Research Center (AWCC), The University of Electro-Communications
1–5–1 Chofugaoka, Chofu, Tokyo 182–8585, Japan
Email: {aruga, fujii}@awcc.uec.ac.jp

***Abstract*—In recent years, with the development of wireless communication technologies, various applications use the same networks and complexity of the networks becomes large. Until now, the protocols and parameters used in networks have been determined by humans based on their experience, but the performance degradation due to the inability to adapt to various applications in various environment especially in wireless condition. To solve this problem, a wireless MAC protocol is needed that can adapt to various environments and applications by allowing the network to control itself autonomously. The proposed method collects the information of each node in the gateway (GW) and learns by deep reinforcement learning DQN to adaptively select the parameters of MAC protocols according to the environment. In addition, assuming an environment in which a video streaming application using adaptive bitrate (ABR) is running on each node, the proposed method improves QoE by selecting an appropriate bitrate. We show that the proposed method improves the average throughput and QoE compared to CSMA/CA without parameter adjustment. To evaluate the performance of the proposed method, we compare the performance of the proposed method with CSMA/CA without parameter tuning by using computer simulations. From the simulation results, it is confirmed that the proposed method can obtain higher average throughput and QoE than the protocol without parameter adjustment.**

***Index Terms*—Deep Reinforcement Learning, DQN, Network Protocol**

I. INTRODUCTION

Recently, with the development of wireless communication technologies, the network has become large-scale and complicated. Communication by Internet of Things (IoT) devices, in which various applications are connected to the Internet, is rapidly increasing. According to the report in [1], the number of devices connected to the Internet is expected to exceed 29.3 billion by 2023. With the popularization of various devices such as IoT devices, the environment in which the network is placed becomes complicated, and the targets to be achieved by the network such as improvement of throughput and reduction of power consumption are diversified. Until now, the protocol used in the network and the parameters are decided by the humans based on experience. However, the various applications and various environment cannot be treated by simple hierarchical network protocols in future complicated wireless networks. Therefore, to solve this problem, a wireless MAC protocol that can be adapted to various environments and applications by controlling parameters and protocols autonomously is required.

Reinforcement learning is one of the methods to control the system autonomously. Reinforcement learning is a method suitable for making decisions without human intervention in an unknown environment. Deep reinforcement learning, which enables learning in more complex environments by using deep neural networks, has been used in research on optimization of various protocols [2] [3]. However, many of these studies focus on adapting a single parameter, and few focus on adapting multiple parameters or switching protocols over considering multiple network layers. The fixed use of existing MAC layer protocols such as ALOHA and carrier sense multiple access and collision avoidance (CSMA/CA: Carrier Sense Multiple Access/Collision Avoidance) is not always appropriate in diverse environments. In addition, the conventional approach does not consider the behavior in the application layer, and it may be difficult to improve the performance depending on the application actually running on the node. Machine learning using neural networks is one of the approach to solve problems.

In this paper, we propose an adaptive control method of wireless MAC protocol considering the application layer in distributed systems. In the proposed method, information such as the number of devices and the number of retransmissions is collected from each node. The functions such as carrier sense and parameters such as RTS/CTS are selected autonomously by using learning at the gateway (GW), according to the environment, and parameters of applications running on nodes are controlled simultaneously. In order to evaluate the effectiveness of the proposed method, we derive the throughput by using computer simulations, in environments with different numbers of devices and networks. From the results of that the proposed method can improve communication quality.

II. MAC PROTOCOL FOR DISTRIBUTED WIRELESS NETWORKS

CSMA/CA is one of the multiple access schemes used in environments with multiple nodes. In CSMA/CA, before each node starts transmitting data, the surrounding node transmission status is checked by carrier sense whether other nodes around it are transmitting data. Therefore, the packet collision is avoided by transmitting data at the timing when other nodes are not transmitting data. If the frequency band is already in use, the Contention Window (CW) value and the wait time determined by the backoff algorithm must elapse before transmission is attempted again. The value of CW is determined from a preset minimum value CWmin and a preset maximum value CWmax. Initially, the value of CW is CWmin, which is increased by the backoff algorithm when packet collisions occur. If multiple packet retransmissions occur and the CW value reaches CWmax, the CWmax value is used until transmission succeeds or the maximum number of retransmissions is reached. Each node determines a random wait time from the value of the CW before transmitting the packet, so that the node with the shortest wait time can transmit the packet. Other nodes carry over the remaining waiting time to the next packet transmission, so that a plurality of nodes can communicate while avoiding collision. Backoff algorithms include Binary Exponential Backoff (BEB), which is used in IEEE 802.11, and Exponential Increased Exponential Decreased (EIED), which moderates CW changes [4].

CSMA/CA is a protocol often used in distributed systems, but the environment in which the network is placed (e.g., number of nodes, presence of hidden nodes, etc.) varies, and fine parameter tuning is required to improve the performance of a generic protocol such as CSMA/CA. For example, in the CSMA/CA, there exists a hidden terminal problem in which the collision avoidance mechanism by the carrier sense does not function in a situation where there are nodes which cannot detect communication with each other, and collisions frequently occur, and in an environment where the number of nodes is small, the overhead by the carrier sense causes performance degradation. Therefore, in an environment where hidden nodes exist, RTS/CTS may be used, and in an environment where the number of nodes is small, the overhead may be reduced by using a constant value for CW or by not performing carrier sense, such as ALOHA, thereby improving communication performance.

III. SYSTEM MODEL

The system assumed in this study is shown in Fig. 1. We assume an environment in which GW exists in the center of the communication area of $D \times D\,[\mathrm{km}^2]$, and N nodes are randomly located around it. On each node, an video streaming application with an adaptive bitrate (ABR) is executed. In ABR, the bitrate can be changed during the reproduction of the video. As shown in Fig. 2, the video data stored on the video distribution server is divided into multi-second units called chunk in advance, and further encoded at a plurality of bitrates. The node downloads video data in chunks. At this time, the node can select a bitrate different for each chunk as shown in Fig. 3 according to the communication bandwidth and buffering time.

QoE is commonly used to assess communication quality in ABR applications. In this study, we use ITU-T Recommendation P.1203 [5], which is standardized for ABR applications, to calculate QoE. P.1203, QoE is estimated from information such as bitrate, resolution, and rebuffering frequency. The maximum resolution of the video distributed in this system is Full HD, and half of the device types of the nodes are PC/TV and the other half are mobile. QoE is calculated on the nodes and aggregated to the GW.

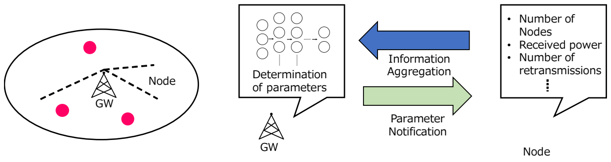

Fig. 1. System model.

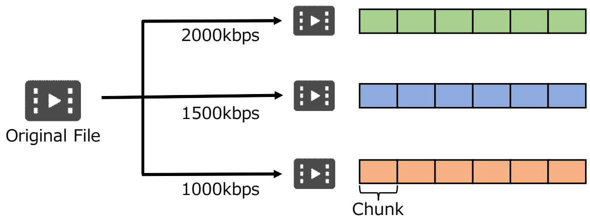

Fig. 2. Adaptive BitRate.

GW has a neural network with 3 intermediate layers with 62 intermediate nodes. The activation function uses ReLU to output the Q value of the action using ε -greedy. The inputs and outputs of the neural network are described in Chapter IV.

IV. PROPOOSED METHOD

A. MAC Parameter Adaptation

First, in order to improve the performance of the MAC protocol, parameters of the MAC protocol are initially selected. The GW gathers received power, retransmission frequency, current parameters, and channel usage from each node. The GW learns the collected information as input value and average throughput as reward by DQN (Deep Q-Network), and selects the next state so as to maximize the reward among all available states. The output states include the MAC parameters used by each node. The output MAC parameters are shown in Table I. Here, all nodes use the parameters selected in the GW and use the same value whether carrier sense is on or off. Because MAC protocol parameters are dependent on each other, each output checks to see if the correct parameters and functions are selected. For example, you cannot use RTS/CTS without carrier sense, but you can use carrier sense without RTS/CTS.

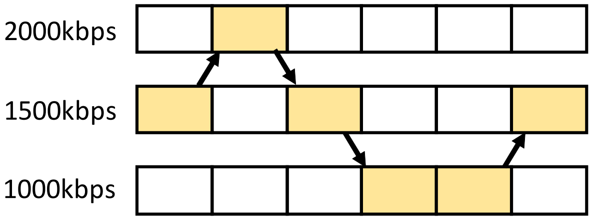

Fig. 3. Example of Bitrate Selection with ABR.

TABLE I
OUTPUT PARAMETERS OF MAC LAYER

Adapted Item	Parameters
Career Sense	on, off
CW Max.	3, 4, 5, $\cdots$, 15, 31, 63, 127, 255, 511, 1023
CW Min.	3, 4, 5, $\cdots$, 15, 31, 63, 127, 255, 511, 1023
RTS/CTS	on, off
Backoff Algorithm	off, BEB, EIED

TABLE II
SIMULATION PARAMETERS

Number of Nodes	1, 4, 7, $\cdots$, 25
Area Size	20×20 [m^2]
Frequency	5.2 [GHz]
Packet Length	1500 [bytes]
Slot Time	9 [μ s]
SIFS	10 [μ s]
DIFS	34 [μ s]

B. Application Parameter Adaptation

The ABR application requests a maximum bitrate equal to or less than the predicted band from the information of its own buffer time and throughput. In this case, rebuffering may occur and some nodes may occupy the bitrate. Then, by instructing the node on a guideline for bitrate selection from GW, bitrate selection is performed while suppressing occurrence of rebuffering and video quality variation. The GW collects device type, screen resolution, past selection bitrate, past rebuffering event occurrence number and QoE history from each node, and performs learning by DQN using the QoE of the whole system as a reward, thereby outputting the range of selection bitrate and the positivity of quality change in each node.

After the adaptation of the ABR application is finished, the parameters of the MAC layer are controlled by learning again using QoE as a reward. Thus, the MAC parameter is changed so as to obtain a higher QoE by flexibly assigning a band to a node, for example, a wider band to a node with a higher screen resolution.

V. SIMULATION EVALUATION

Computer simulations are performed by varying the environment and the number of nodes. Simulation parameters are shown in Table II. CSMA/CA and standard ABR algorithms compliant with IEEE802.11 are used as the comparison method.

First, Fig. 4 shows the average throughput by changing the number of nodes. By adapting the parameters of the MAC layer, it can be seen that the proposed method achieves high average throughput at any number of nodes. TABLE III shows selected MAC parameters for each number of nodes in the proposed method. In an environment with a small number of nodes, the overhead is reduced by changing the MAC protocol functions and parameters according to the network load, such as turning off the carrier sense or changing the CW Max. and CW Min. thereby contributing to improved communication performance.

TABLE III
EXAMPLE OF SELECTED MAC PARAMETERS

Number of Nodes	1	4	7	$\cdots$	22	25
Carrier Sense	off	off	on	$\cdots$	on	on
CW Min.	6	11	15	$\cdots$	31	15
CW Max.	-	-	127	$\cdots$	255	127
RTS CTS	off	off	off	$\cdots$	off	on
Backoff Algorithm	off	off	EIED	$\cdots$	BEB	BEB

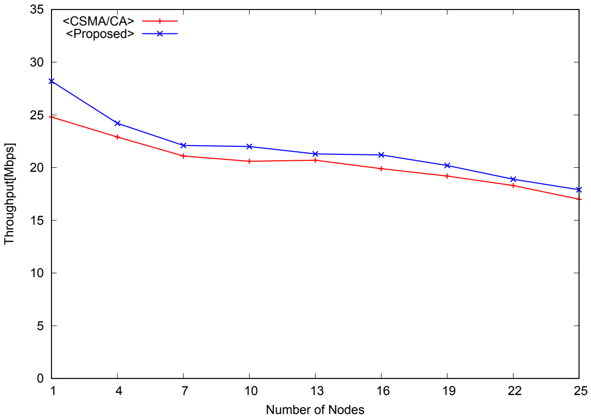

Fig. 4. Average Throughput.

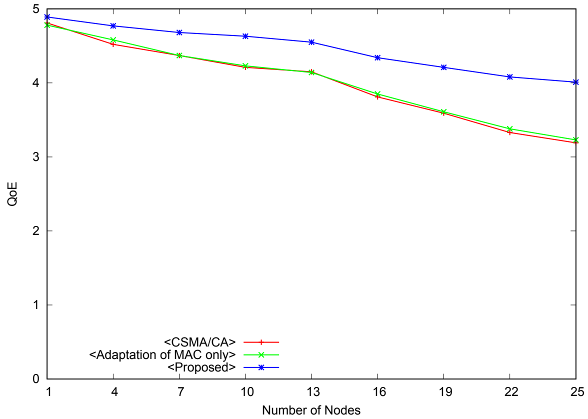

Fig. 5. Average QoE.

Fig. 5 shows QoE for each number of nodes when only the MAC layer learning is applied and when both MAC layer learning and application layer learning are applied. Although the improvement of communication performance by adapting the parameters of the MAC layer alone does not show a significant QoE improvement, the proposed method including the adaptation of ABR suppresses the reduction of QoE even in an environment with a large number of nodes.

VI. CONCLUTION

In this study, we propose an adaptive parameter selection method in the MAC protocol and an adaptive bitrate selection method in the ABR application according to the environment using deep reinforcement learning. In addition, QoE without parameter adjustment is calculated, and it is confirmed that the proposed method can maintain high QoE.

In the future, we will consider improving QoE in environments where the purpose of communication per node is mixed by considering multiple applications and corresponding learning rewards.

VII. ACKNOWLEDGMENT

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