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Research on Resource Allocation Under Edge Intelligence

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Abstract

In recent years, the marginalization of computing infrastructure has gradually become a new trend in the development of computing architecture technology. Under the influence of this trend, the perception and computing mode based on edge computing has been promoted. Therefore, edge computing is also considered as the key technology of the next generation Internet. Compared with the traditional cloud center computing mode, the edge computing mode hands over some computing tasks to edge devices with computing power for processing, which not only reduces the computing pressure and IO pressure of the cloud center server, but also improves the system response speed, enabling users to get better Quality of Experience (QoE). At the same time, edge computing also brings new challenges to network architecture, data transmission, resource allocation, model deployment, data security, etc. In this paper, we study the resource allocation problem in the edge network, and propose an adaptive bandwidth allocation algorithm based on reinforcement learning, which better solves the network resource allocation problem of multiple devices in the edge network.

Keywords

Edge Computing; Edge Intelligence; Adaptive Streaming.

1. INTRODUCTION

With the progress of technology, the video traffic on the Internet has been increasing rapidly in the past two decades. HTTP Adaptive Streaming (HAS) is the mainstream protocol in the field of video transmission. Among the many implementation mechanisms of HAS, the DASH (Dynamic Adaptive Streaming over HTTP) protocol developed under the auspices of the Motion Picture Expert Group (MPGE) has become an important implementation of HAS and an international standard at present. In the HAS scenario, video is compressed into video segments with different bit rates and stored on the server. The video player requests video segments with different bit rates according to the current available bandwidth. Since each video player tends to request the best video segment according to the current available bandwidth, resource competition will occur in multi-player scenarios, which may lead to unfair bandwidth allocation (some players are in a state of hunger for a long time) and insufficient bandwidth utilization.

This paper studies the bandwidth adaptation of multi-player environment in the context of reinforcement learning, and designs an edge network-oriented adaptive streaming media transmission framework, which aims to provide a fair bandwidth environment for multiple players in the LAN and try to ensure the QoE fairness of users. We segment the video at different bit rates, collect the bit rate request information on the network side, and use the OpenFlow switch to allocate bandwidth to LAN users. The core of the transmission framework is the Sarsa algorithm. The test results show that compared with the current mainstream methods, our solution can make reasonable use of the environment bandwidth, bring a more stable bit rate switching experience, and better achieve the QoE fairness of users.

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2. METHODS

2.1. Problem Analysis

At present, there are three solutions for fair video transmission in DASH system. The first is the intra-network solution, that is, SDN technology used in literature, which ensures the QoE of users by monitoring the information of client players and networks [7], [8], [9]. The second solution is the client solution, which uses bandwidth estimation and video segment scheduling to improve DASH performance [10], [11]. But if the network indicators are not visible, this solution cannot be implemented. The third is the server-side solution. The literature proposes a server-based flow control method [12]. Which can significantly reduce network fluctuations, but the bottleneck bandwidth will not only appear at the server, but also may appear elsewhere in the network.

2.2. Build model

Figure 1 is a real network model. We can simplify it to the bandwidth allocation model shown in Figure 2.

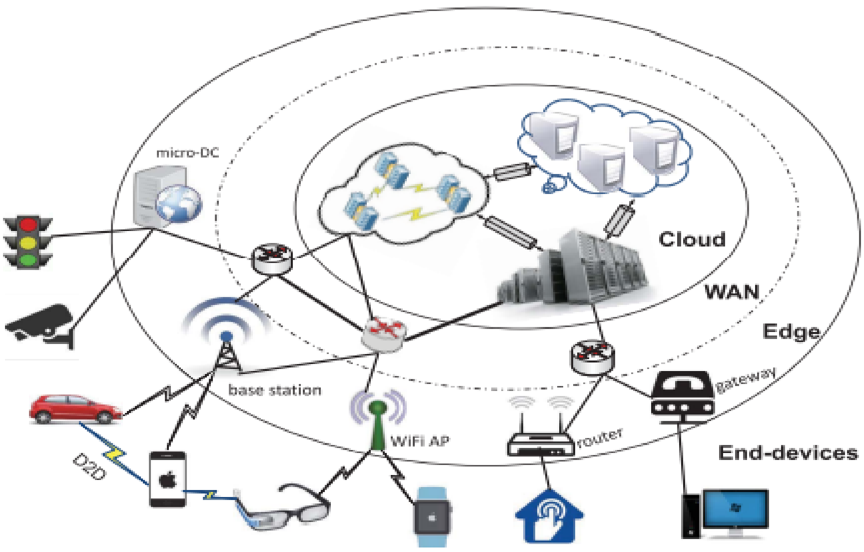

Figure 1. Real network model

We assume that there is a LAN environment with multiple DASH users, and the number of users is N. Assuming that the bottleneck bandwidth at time t is B(t), let $bw_i(t) \in R_+$ indicate the available bandwidth of user i at time t, due to the bandwidth loss caused by the network, we can conclude that:

$$\sum_{i \in N} bw_i < B_t \tag{1}$$

We precoder the video into a set of G bit rates BR, and set a level for each bit rate, expressed by $lr \in G$, user i selects different bit rates for the video fragmentation according to the current estimated bandwidth, so $br_i(t) \in BR, lr_i(t) \in G$

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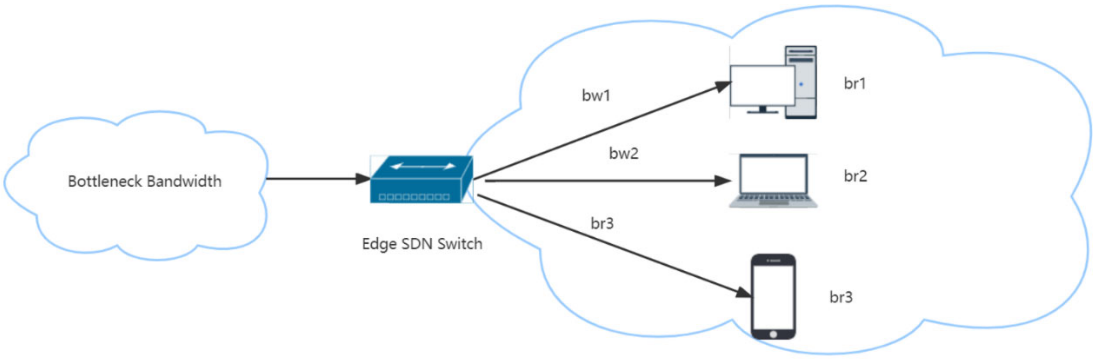

Figure 2. Abstract network model

For fairness of multiple DASH users, their goal is to maximize QoE fairness. We choose user-level indicators to measure QoE fairness, mainly including video quality fairness VQ (t) and bit rate switching fairness VS (t). We use the relative standard deviation (RSD) of the sharding bit rate level requested by the user to measure the system bandwidth stability.

Our goal is to maximize the fair utility value of the QoE. Therefore, QoE fairness oriented to multiple users model is as follows:

$$max\sum_{t=0}^{\infty}Fairness(t) \tag{2}$$

Because the model is a long-term planning problem, we designed a QoE fair bandwidth allocation algorithm based Sarsa.

2.3. SDBA

The SDBA(Sarsa Dynamic Bandwidth Allocation) algorithm is implemented based on reinforcement learning, so the state, action and reward function should be designed first. The key values of the environment state are the request bit rate br_i and bottleneck bandwidth B of each user i. We divide br_i and B into G groups to avoid dimension explosion. where spw = B_{max}/G , $b \in \{0,1,2 \dots G-1\}$ and $spr = (lr_{max}+1)/G$, $lr_i \in \{0,1,2 \dots G-1\}$. State S = $(s_1, s_2 \dots s_t)$, s_t includes the bottleneck bandwidth group b and the bit rate level requested by each player user i in each step.

$$s_t = (b, lr_1, lr_2 \dots lr_N) \tag{3}$$

If the action set of bandwidth allocation to users A=$(a_1, a_2 \dots a_t), a \in R_+$, this will lead to dimension explosion. In order to discretize the action space, we will discretize the bandwidth allocated to users. Therefore, we introduce an action mapping set $M_a(b)$ = {0, 1, … , G}

$$a_t = (m_{a_1}, m_{a_2}, \dots, m_{a_N}) \tag{4}$$

Reward is the long-term goal of reinforcement learning method. We choose the following diminishing function as the reward function.

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$$r_t = e^{-(w_1 VQ(t) + w_2 VS(t))} \tag{5}$$

w_1 and w_2 are the weight parameters of the two indicators. The value of the reward can be a positive number indicating that the QoE fairness condition of the end user player is good. A negative number indicates that the end user player QoE has poor fairness conditions. The specific implementation details are shown in the Figure3.

SDBA Algorithm

1 Initialize $Q(s_0, a_0), \forall s_0 \in S, \forall a_0 \in A$
2 Repeat (When BW change:)
3 Observe s_t, Choose $a_t \in A$, based on S from Q (using Softmax)
4 Take action a_t according to the b by add flowtable to set port dif bandwidth queue for each egress port.
5 Observe $lr_i, lr_{N_{t-1}}$ and new state s_{t+1}
6 Compute $r_t = e^{-(w_1 VQ(t) + w_2 VS(t))}$
7 Update $Q(s_t, a_t) = (1-\alpha)Q(s_t, a_t) + \alpha[r_{t+1} + \gamma Q(s_{t+1}, a_{t+1})]$

Figure 3. SDBA

3. RESULTS

To verify our algorithm, we designed and implemented a prototype system based on Mininet, the system includes three DASH players and an HTTP server, which is used to store DASH video, the bottleneck bandwidth fluctuates between 0.7 $M\ b/s$ and 12 $M\ b/s$ in a fixed mode, the system operation time is 300 seconds. In order to evaluate the SDBA algorithm, we also adopted the QFF bandwidth average allocation method proposed in document as the baseline method [13].

Within a fixed duration, we compared the playback progress of different strategies shown in Figure 4 and Figure 5. The playback progress is indicated by the number of downloaded videos. QFF method can improve the fairness of the system to a certain extent, but there will be a more fluent phenomenon for users. Our method SDBA shows the best fairness of the playback progress.

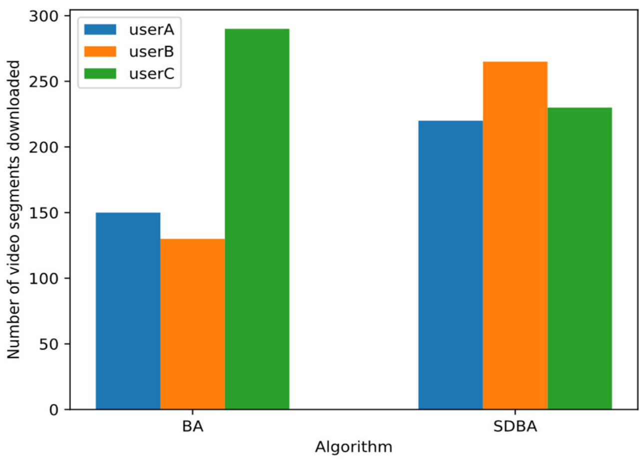

Figure 4. Play progress of two algorithms

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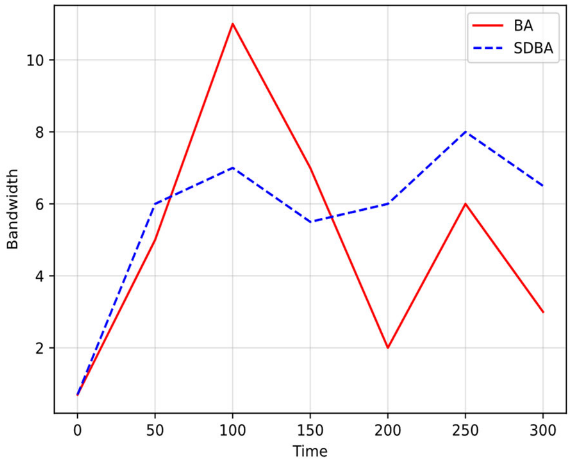

Figure 5. Bandwidth obtained by one player

4. CONCLUSION

In recent years, the network computing model has gradually changed from cloud computing to edge computing. The main feature of edge computing is to migrate computing and caching to the user side, so it is very common for multi users to compete for bandwidth in edge networks. One of the main research directions of this paper is resource adaptation in edge networks. Using the current popular next-generation network technology SDN, we designed a network-driven QoE fairness framework.

In this paper, we designed and implemented a prototype system based on reinforcement learning, and carry out experimental tests. The experiment shown that compared with the baseline method, the SDBA algorithm can ensure better network stability, reduce network fluctuations under the edge system, provide fair bandwidth allocation and smooth switching experience, give users better playback experience, and achieve better user QoE.

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