

Chapter 25

User–Oriented Video Streaming Service Based on Passive Aggressive Learning

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ABSTRACT

The authors propose a method to dynamically determine appropriate quality of service (QoS) required by users for video streaming services. In the proposed method, the video bit rate as the QoS parameter is determined based on the passive aggressive learning, which is an online learning algorithm for a regression problem, according to the user requirements, computational/network resources and service provisioning environments. Moreover, the method makes it possible to provide appropriate QoS by using optimization solution. In this paper, the authors describe the design and implementation of the method, then confirm the feasibility of the proposed method through the experiments.

DOI: 10.4018/978-1-7998-2460-2.ch025

INTRODUCTION

Over-The-Top (OTT) services provided by service providers unrelated to telecommunication companies or Internet Service Providers (ISPs) on the Internet have spread explosively. Video streaming service that is one of the OTT services for portable devices, such as smartphones, also spreads gradually. (Cisco Systems, 2016) forecasted IP video traffic would be 82% of all consumer Internet traffic by 2020, up from 70% in 2015, and smartphone traffic would exceed PC traffic by 2020. The increased traffic load causes network congestion, which impacts Quality of Service (QoS). The QoS degradation affects packet loss, delay, jitter and throughput (Sugeng, Istiyanto, Mustofa, & Ashari, 2015). Moreover, portable devices have the limited amount of computational and network resources as compared to standard PCs, which has a problem of degrading QoS. For instance, video streaming services for the portable device are normally provided in low quality, and the service continuity is short due to low battery life.

Portable devices are vulnerable to interference from surrounding environments because of wireless network connections; therefore, the network resources are insufficient and unstable as well. With increasing demands for high quality video contents, 4K and 8K videos are widespread rapidly; however, their contents are mainly compressed by H.265/HEVC (High Efficiency Video Coding) that can provide twice the compression efficiency of H.264/AVC (Advanced Video Coding) (Hankinson, 2013). Since HEVC requires the powerful computational resources, it is challenging for portable devices to adopt new resolutions and frame rates (Crestron, 2014). As for standard PCs, to avoid the shortage of computational resources, service users need to select an appropriate video quality from a few pre-defined video quality list in conventional video streaming services. Consequently, in terms of portable devices, it would be more difficult for all service users to receive services with satisfying QoS that matches user requirements since the QoS selection is more restricted.

To deal with this problem, current video streaming services use HTTP-based Adaptive Streaming (HAS) methods (Oyman & Singh, 2012), such as Microsoft Smooth Streaming (SS), Apple HTTP Live Streaming (HLS), Adobe HTTP Dynamic Streaming (HDS) and Dynamic Adaptive Streaming over HTTP (MPEG-DASH). These methods stream video contents with the appropriate QoS depending on the network status. (Satake & Bandai, 2013, 2015) have proposed a stream scheduling method in which the Structural SIMilarity (SSIM) index is maximized depending on the network throughput, and compared with MPEG-DASH. The proposal is effective; however, in some cases, it provides the excessive QoS because of providing maximum video quality at all times. Moreover, as a side effect, the adaptive streaming adversely affects other service users at the same time because of increasing the network traffic.

The authors are aiming to provide video streaming services satisfying various user requirements with reducing the excessive network traffic to solve the problem mentioned above. In order to achieve this purpose, the authors have proposed some methods to determine the QoS dynamically and automatically based on the concept of Symbiotic Computing (Suganuma, Sugawara, Kinoshita, Hattori, & Shiratori, 2009; Uchiya, Maemura, Hara, Sugawara, & Kinoshita, 2009). These methods induce the appropriate QoS considering situation of computational resources of portable devices and the network status. However, service providers need to set thresholds to specify QoS based on various service utilization environments and device resources, or to describe service-expert knowledge for QoS improvement. This causes another problem for service providers to increase their burden.

In this work, the authors propose a novel method to determine the appropriate QoS required by service users depending on computational resources and the network status by using a machine learning technique. Specifically, the method performs Passive Aggressive (PA) learning, which is an online learning

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