Subjective and Objective Quality-of-Experience of Adaptive Video Streaming

by

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

With the rapid growth of streaming media applications, there has been a strong demand of Quality-of-Experience (QoE) measurement and QoE-driven video delivery technologies. While the new worldwide standard dynamic adaptive streaming over hypertext transfer protocol (DASH) provides an inter-operable solution to overcome the volatile network conditions, its complex characteristic brings new challenges to the objective video QoE measurement models. How streaming activities such as stalling and bitrate switching events affect QoE is still an open question, and is hardly taken into consideration in the traditionally QoE models. More importantly, with an increasing number of objective QoE models proposed, it is important to evaluate the performance of these algorithms in a comparative setting and analyze the strengths and weaknesses of these methods.

In this study, we build two subject-rated streaming video databases. The progressive streaming video database is dedicated to investigate the human responses to the combined effect of video compression, initial buffering, and stalling. The adaptive streaming video database is designed to evaluate the performance of adaptive bitrate streaming algorithms and objective QoE models. We also provide useful insights on the improvement of adaptive bitrate streaming algorithms.

Furthermore, we propose a novel QoE prediction approach to account for the instantaneous quality degradation due to perceptual video presentation impairment, the playback stalling events, and the instantaneous interactions between them. Twelve QoE algorithms from four categories including signal fidelity-based, network QoS-based, application QoS-based, and hybrid QoE models are assessed in terms of correlation with human perception

on the two streaming video databases. Experimental results show that the proposed model is in close agreement with subjective opinions and significantly outperforms traditional QoE models.

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Chapter 1

Introduction

1.1 Motivations

In the past decade, there has been a tremendous growth in streaming media applications, thanks to the fast development of network services and the remarkable growth of smart mobile devices. Since the ratification of the MPEG-DASH standard in 2011 [72], video streaming providers have invested significant effort in the transition from the conventional connection-oriented video transport protocols towards HTTP adaptive streaming protocols (HAS) due to its ability to traverse network address translations and firewall, reliability to deliver video packet, flexibility to react to volatile network conditions, and efficiency in reducing the server workload. DASH [10] achieves decoder-driven rate adaptation by providing video streams in a variety of bitrates and breaking them into small HTTP file segments. The media information of each segment is stored in a *manifest* file, which is created at server and transmitted to clients to provide the specification and location of

each segment. Throughout the streaming process, the video player at the client adaptively switches among the available streams by selecting segments based on playback rate, buffer condition and instantaneous TCP throughput [72]. Adaptive bitrate streaming (ABR) algorithms, that determine the bitrate of the next segment to download, are not defined within the standard but deliberately left open for optimization of the algorithms. The key to developing the optimal ABR algorithm is to define an optimization criterion that aims at maximizing viewer quality-of-experience (QoE). Here QoE refers to the overall viewer satisfaction of the playback experience of the video stream at the client's receiving and display device. QoE is centralized on human experience at the end of the video delivery chain, and is different from the concepts of quality-of-service (QoS) or quality-of-delivery (QoD), which focuses on the service level and stability of the video transmission process through the network, and is often measured by network service and performance parameters such as bandwidth, bit error rate, packet loss rate, and transmission delay.

Over the past decade, ABR has been a rapidly evolving research topic and has attracted an increasing amount of attention from both industry and academia [30, 46, 40, 81, 12, 35, 85, 5]. We need to thoroughly understand realistic impairment patterns with the help of the most commonly used ABR algorithms. As human visual system (HVS) is the ultimate receiver of streaming videos, subjective evaluation is the most straightforward and reliable approach to evaluate the QoE of streaming videos. The understanding of HVS would inspire development and validation of objective video QoE assessment methods. Furthermore, with many ABR algorithms at hand, it becomes pivotal to compare their performance, so as to find the best algorithm as well as directions for further improvement.

Even though subjective quality assessment studies provide reliable evaluations, they are

inconvenient, time-consuming, and expensive. Most importantly, they are not applicable in the real-time playback scheduling framework. Therefore, highly accurate, low complexity objective models are desirable to enable efficient design of quality-control and resource allocation protocols for media delivery systems. Over the past decade, substantial effort has been made to develop objective QoE models [78, 80, 63, 55, 58, 82, 29, 28, 53, 61, 84, 26, 68, 83, 59]. Most of them are designed for specific applications such as static video quality assessment or progressive video streaming. Thus, an objective QoE model that can accurately predict the subjective QoE is highly desirable.

In addition, no QoE validation literature has previously reported comprehensive comparative performance of different objective QoE models. It is therefore important that objective QoE algorithms be tested on extensive ground truth data if they are to become widely accepted. Furthermore, if this ground truth data, apart from being extensive in nature, is also publicly available, then other researchers can report their results on it for comparative analysis in the future.

1.2 Objectives

The objectives of this thesis are to carry out subjective testing and develop advanced QoE models accurately predict the subjective perceived satisfaction of HAS, and to systematically investigate the performance of existing objective QoE algorithms and ABR algorithms.

1.3 Contributions

The major contributions of this thesis are summarized as follows.

- We construct two subject-rated streaming video databases. The first database is dedicated to the combined effect of initial buffering, stalling and video compression on QoE, which is one of the first publicly available databases of its kind. Our experiments show that the video presentation quality of the freezing frame exhibits interesting relationship, which has not been observed before, with the dissatisfaction level of the stalling event. The second video database is the first large-scale database dedicated to subjective evaluation of HAS videos under realistic settings and evaluation of objective QoE models. Based on the subjective responses on streaming videos, we provide useful insights on the improvement of ABR algorithms.

- We formulate a joint video streaming QoE model that incorporates both the video presentation quality and the influence of playback stalling. Based on the two databases, we conduct by far the most comprehensive evaluation on the objective QoE models. Twelve QoE algorithms from four categories including signal fidelity-based, network QoS-based, application QoS-based, and hybrid QoE models are assessed in terms of correlation with human perception. Statistical hypothesis tests are also performed to compare QoE models in a statistically meaningful manner. Extensive experiments on the benchmark databases show that the proposed model significantly outperforms existing QoE models. In the end, we shed light on the development objective QoE measurement algorithms and practical deployment of real-time QoE monitoring systems throughout the delivery chain. The results have significant im-

plications on how content providers can best use their resources to maximize user perceived QoE and how should a practical real-time QoE monitoring system be deployed.

1.4 Thesis Outline

The layout of this thesis is organized as follows.

Chapter 2 discusses the related work in the literature. It starts with a brief introduction about the subjective QoE studies and existing publicly available video quality databases. We then perform a brief overview of existing objective QoE models.

Chapter 3 presents in detail the design of the two streaming video databases and subjective experiments. From the analysis of the subjective response to the streaming videos, we illustrate the interaction between stalling and video quality, and evaluate the performance of ABR algorithms.

In Chapter 4, we propose a joint video streaming QoE model that incorporates both the video presentation quality and the influence of playback stalling. In order to evaluate the performance of the proposed QoE model, we present by far the most comprehensive comparative study on the performance of objective QoE models. In the end, we shed light on the practical real-time QoE monitoring frameworks throughout the delivery chain.

Finally, Chapter 5 summaries the work that has been done so far and discusses different avenues for future research.

Chapter 2

Literature Review

2.1 Subjective QoE Studies

Several well-known QoE databases have been widely used in the literature. In 2012, Moorthy *et al.* conducted a subjective video quality study on mobile devices and created the LIVE mobile video quality assessment database (LIVEMVQA) [49] that consists of ten reference and two hundred distorted videos with five distortion types: H.264 compression, stalling, frame drop, rate adaptation, and wireless channel packet-loss.The single-stimulus continuous scale method [32] is adopted for testing, where both the instantaneous ratings as well as an overall rating at the end of each video is collected. It is the first publicly available subject-rated video database that contains various types of practical distortions in the streaming process. However, the distortion types of video sequences are isolated and hence, the conclusions of the studies may not be directly transfered to the combined degradations.

LIVE QoE database for HAS (LIVEQHVS) [6] contains three reference videos constructed by concatenating eight high quality high definition video clips of different content. For each reference video, five bitrate-varying videos are constructed by adjusting the encoding bitrate of H.264 video encoder resulting 15 quality-varying videos. Based on the continuous-time subjective ratings, Chen *et al.* recognize the importance of the hysteresis effect and nonlinear perception of the time-varying video quality. Following a similar subjective experiment setup to LIVEMVQA, the authors collect both the instantaneous ratings and an overall rating at the end of each video. However, the small number of video sequences in the database limits its current utility.

Ghadiyaram *et al.* [25] perform a subjective study to understand the influence of dynamic network impairments such as stalling events on QoE of users watching videos on mobile devices. The constructed database (LIVEMSV) consists of 176 distorted videos generated from twenty-four reference videos with twenty-six hand-crafted stalling events. The authors adopted the single stimulus continuous quality evaluation procedure where reference videos are also evaluated to obtain a difference mean opinion score (DMOS) for each distorted video sequence. However, some of the stalling patterns are not realistic in practical HAS services. For example, two consecutive stalling events must have a minimum temporal separation with the duration of one segment in most of the ABR algorithms. In addition, the lack of video compression and quality switching reduce the relevance of the work to HAS. A summary of the aforementioned databases are given in Table 2.1.

Several other streaming video quality studies have been conducted in the past, mainly towards understanding the effects of network stream quality on QoE, validating the performance of ABR algorithms, and developing objective QoE models. Pastrana *et al.* [54]

Table 2.1: Comparison of publicly available QoE databases for adaptive video streaming

Database	# of Source Videos	# of Test Sessions	HAS-related Impairments
LIVEMVQA	10	200	switching or stalling
LIVEQHVS	3	15	switching
LIVEMSV	24	176	stalling
Waterloo SQoE-I	20	180	initial buffering or stalling
Waterloo SQoE-II	20	450	initial buffering & stalling & switching

made one of the first attempts to measure the impact of stalling in video streaming services. The study showed that QoE is influenced by both the *duration* and the *frequency* of stalling events and was confirmed by Qi *et al.* [56]. Among those findings, the most important one is that viewers tend to prefer videos that have less number of freeze events (even if they are relative longer) to videos that have a sequence of short freezes through time. Besides, Qi *et al.* [56] also found that a stalling of frame-level duration could not be perceived, and thus has no impact on QoE. Staelens *et al.* [71] extended Qi's research and conclude that isolated stallings up to approximately 400 ms is acceptable to the end-users. Moorthy *et al.* [49] investigated the trade-off between stalling and quality switching. While many studies [20][4] assumed that stalling events are more annoying than quality switches, the results in [49] showed that few stalling events are not yielding worse quality than downward quality switches. Hoßfeld *et al.* [27] and Sackl *et al.* [62] found fundamental differences between initial delays and stalling. Unlike initial delay which is somewhat expected by today's consumers, stalling invokes a sudden unexpected interruption and distort the temporal video structure. Hence, stalling is processed differently by the human sensory system, *i.e.*, it is perceived much worse [18]. Garcia *et al.* [23] investigated the quality impact of the combined effect of initial loading, stalling, and compression for high definition sequences, from which they observed an additive impact of stalling and com-

pression on perceived QoE. Besides the effect of video impairment itself, Seshadrinathan *et al.* [64] described a hysteresis effect in a recent study of time-varying video quality. In particular, an unpleasant viewing experience in the past tends to penalize the QoE in the future and affect the overall QoE. However, the unavailability limits the usefulness of the databases. Two excellent surveys on subjective QoE study can be found in [66] and [22].

Based on these subjective user studies, one may conclude that: 1) video presentation quality, duration and frequency of stalling are the key factors contributing towards the overall QoE; 2) Although very short stalling may not be perceived and thus has little impact on QoE, visible stalling events can severely degrade QoE; 3) Viewers are much more tolerant to initial buffering than stalling; 4) An unpleasant viewing experience in the past tends to penalize future QoE.

However, all of the above studies suffer from the following problems: (1) the interaction between video presentation quality and stalling experience is not investigated, (2) the dataset is of insignificant size, (3) hand-crafted stalling and quality switching patterns do not reflect realistic scenarios in the HAS, (4) the distortion types of video sequences are isolated, (5) spatial resolution adaptation that is commonly used in the HAS is not presented, and (6) the bitstream and network information, which are valuable to the development of ABR algorithms and objective QoE models, are not available. Realizing the need for an adequate and more relevant resource, we have endeavored to create databases of broader utility for modeling and analyzing contemporary HAS.

2.2 Objective QoE Models

The existing QoE models can be roughly categorized as follows:

- **Signal Fidelity Measurement**

  Objective VQA approaches tackle the QoE problem from a signal fidelity point of view to provide computational models that can automatically predict video presentation quality. In practice, for the sake of operational convenience, bitrate and Quantization Parameter (QP) are often used as the indicators of video presentation quality [2][86][1][10]. However, using the same bitrate or QP to encode different video content can lead to drastically different visual quality. In addition, different encoders operate at the same bitrate or QP but different operational or complexity modes can also cause large quality variations in the compressed video streams. In order to have a better estimation of the user perceived QoE, it is desired to assess the raw video. For this purpose, the simplest and most widely used VQA measures are the mean squared error (MSE) and peak signal-to-noise ratio (PSNR), which are easy to calculate and mathematically convenient, but unfortunately do not correlate well with perceived visual quality [77]. Research in perceptual VQA [79][76] has been drawing significant attention in recent years, exemplified by the success of the structural similarity index (SSIM) [78], the multi-scale structural similarity index (MS-SSIM) [80], motion-based video integrity evaluation index (MOVIE) [63], video quality metric (VQM) [55] and SSIMplus [58]. State-of-the-art VQA models employ human visual system features in quality assessment, and thus provide perceptually more meaningful prediction. Nevertheless, all of these models are only applicable

when the playback procedure can be accurately controlled. However, video streaming services, due to network impairments, may suffer from playback issues that could significantly degrade user QoE. How modern VQA models can be used in the context of HAS is still an open problem.

- **QoE Prediction via Network Quality-of-Service (QoS)**

  The philosophy behind this type of approach is that there exists an causal relationship between generic QoS problems (e.g, loss, delay, jitter, reordering and throughput limitations) and generic QoE problems (e.g., glitches, artifacts and excessive waiting time) [19]. Therefore, QoE can be easily quantified once the mapping function between QoS and QoE is known. Kim [36] found an exponential relationship between QoE and several network QoS parameters such as packet loss, jitter, and bandwidth utilization ratio. Instead of looking for the direct relationship between network QoS parameters to QoE, Mok [47] tried to firstly estimate the application QoS parameters such as stalling time and stalling frequency from the network QoS parameters, and then performed regression analysis to acquire the relationship between QoE and application QoS.

- **QoE Prediction via Application Quality-of-Service**

  Most existing research in this direction are dedicated to *stalling experience quantification*. Watanabe *et al.* [82] attempt to quantify streaming video QoE based on playback stallings. They observed a logarithmic relationship between the global length of stalling events and QoE. Mok *et al.* [47] associated the length and frequency of stalling to QoE with a linear function. Hoßfeld *et al.* [19] [29][28] demonstrated the

superiority of exponential mapping functions in many streaming applications. Although the global QoS statistics-based QoE models are computationally efficient, they ignore the importance of temporal factors. Rodriguez *et al.* [61] consider the pattern of jitter and local content importance by subjective training of the content. Yeganeh *et al.* [84] quantify the stalling experience with a raised cosine function and the recovery of satisfaction level during the playback state with a linear model. Deepti *et al.* [26] employ a Hammerstein-Wiener model using the stalling length, the total number of stalling events, the time since the previous stall, and the inverse stalling density as the key features to predict the instantaneous experience at each moment.

Apparently both video presentation quality and application level QoS capture important aspects in QoE. Unfortunately, very few approaches incorporate the two aspects into a unified model. Liu *et al.* [41] and Yin *et al.* proposed to use both bitrate and stalling duration to predict subjective QoE. Singh *et al.* [68] tried to solve this problem by training a random neural network [24] using QP, frequency, average and maximum duration of stalling events as input features. Xue *et al.* [83] estimated the video presentation quality by QP and weighted the impact of stalling by packet bit count as an indicator of motion complexity. These algorithms define video presentation quality as a function of QP or bitrate, which have been proven to be poor perceptual quality indicators.

- **Hybrid Approach**

  Most existing methods rely on bitrate and global statistics of stalling events for QoE prediction. This is problematic for two reasons. First, using the same bitrate to encode different video content results in drastically different presentation quality.

Second, the correspondence between bitrate and perceptual quality is non-linear. In order to resolve the problems, Liu *et al.* [42] and Bentaleb *et al.* [5] incorporated state-of-the-art VQA algorithms VQM [55] and SSIMplus [58] with stalling duration to predict the subjective QoE.

Despite the demonstrated success, most existing QoE predictors either underestimate the effect of perceptual video presentation quality or simply equate it to bitrate or QP. More importantly, one common assumption of all these approaches is that there is no interaction between video presentation quality and stalling experience, which has not been systematically examined.

Chapter 3

Subjective Quality-of-Experience User Study of Streaming Videos

In this chapter, we construct two subject-rated databases to understand human perceived QoE of streaming videos. We investigate the combined effect of video quality and stalling experience on QoE with the first database, and evaluate the performance of existing ABR algorithms under realistic contisions with the second database.

3.1 Progressive Streaming Video Database

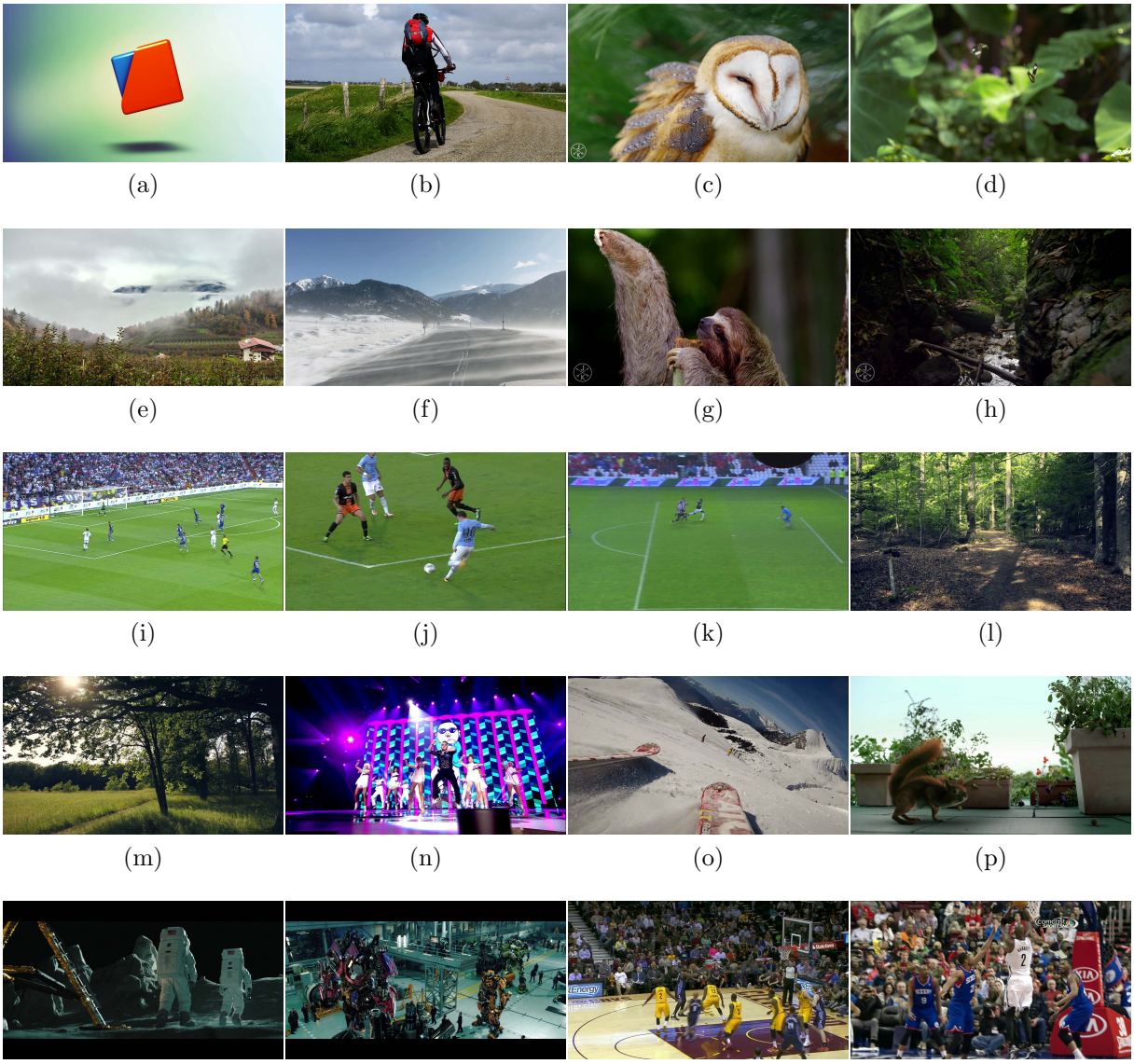
To the best of our knowledge, current publicly available databases are dedicated to either video presentation quality that is affected by compression, channel transmission losses, scaling, or the impact of stalling in terms of its occurring position, duration, and frequency. However, QoE of streaming video should be a joint effect of the video presentation quality

and playback stalling. Although the combined effect of stalling and video bitrate has been investigated by Garcia *et al.* [23], the study suffers from the following problems: (1) the dataset is of insufficient size (6 source sequences); (2) bitrate is not a good indicator of video presentation quality as discussed in the Section 2.2; and (3) the database is not publicly available. Therefore, our goal is to develop a dedicated database to study the interaction between stalling effect and presentation quality for video streaming.

3.1.1 Video Database Construction and Subjective User Study

A video database, named Waterloo Streaming QoE Database I (SQoE-I), of 20 pristine high-quality videos of size 1920×1080 are selected to cover diverse content, including humans, plants, natural scenes, architectures and computer-synthesized sceneries. All videos have the length of 10 seconds [21]. The detailed specifications of those videos are listed in Table 3.1 and a screenshot from each video is included in Fig. 3.1. Using aforementioned sequences as the source, each video is encoded into three bitrate levels (500Kbps, 1500Kbps, 3000Kbps) with x264 encoder to cover different quality levels. The choices of bitrate levels are based on commonly-used parameters for transmission of HD videos over networks. A 5-second stalling event is simulated at either the beginning or the middle point of the encoded sequences. The stalling indicator was implemented as a spinning wheel. In total, we obtain 200 test samples that include 20 source videos, 60 compressed videos, 60 initial buffering videos, and 60 mid-stalling videos.

The subjective testing experiment is setup as a normal indoor home settings with ordinary illumination level, with no reflecting ceiling walls and floors. All videos are displayed



(a) (b) (c) (d)

(e) (f) (g) (h)

(i) (j) (k) (l)

(m) (n) (o) (p)

(q) (r) (s) (t)

Figure 3.1: Subjective test sequences

Table 3.1: Information of reference videos.

Index	Name	Frame Rate	Description
a	Animation	25	animation, high motion
b	Biking	50	human, outdoor
c	BirdsOfPrey	30	natural, static
d	ButterFly	25	natural, outdoor
e	CloudSea1	24	architecture, static
f	CloudSea2	24	outdoor, high motion
g	CostaRica1	25	natural, static
h	CostaRica2	25	natural, static
i	Football1	25	human, high motion
j	Football2	25	human, high motion
k	Football3	25	human, high motion
l	Forest1	25	natural, static
m	Forest2	25	natural, outdoor
n	MTV	25	human, indoor
o	Ski	30	outdoor, high motion
p	Squirrel	25	animation, outdoor
q	Transformer1	24	human, static
r	Transformer2	24	human, architecture
s	Basketball1	25	human, high motion
t	Basketball2	25	human, high motion

at their actual pixel resolution on an LCD monitor at a resolution of 2560 $\times$ 1600 pixel with Truecolor (32bit) at 60Hz. The monitor is calibrated in accordance with the recommendations of ITU-T BT.500 [32]. A customized graphical user interface is used to render the videos on the screen with random order and to record the individual subject ratings on the database. The study adopts a single-stimulus quality scoring strategy. A total of 25 naïve subjects, including 13 males and 12 females aged between 22 and 30, participate in the subjective test. Visual acuity (*i.e.*, Snellen test) and color vision (*i.e.*, Ishihara) are confirmed from each subject before the subjective test. A training session was performed before the data collection, during which, 4 videos (of 1. pristine quality video, 2. 500Kbps

encoded video, 3. video with initial buffering, and 4. video with stalling) were presented to the subjects. We used the same methods to generate the videos used in the training and testing sessions. Therefore, subjects knew what distortion types would be expected before the test session, and thus learning effects are kept minimal in the subjective experiment. Subjects were instructed with sample videos to judge the overall visual quality considering both picture distortion artifacts and video freezes as quality degradation factors. The subjects are allowed to move their positions to get closer or farther away from the screen for better observation. For each subject, the whole study takes about one and half hour, which is divided into three sessions with two 7-minute breaks in-between. In order to minimize the influence of fatigue effect, the length of a session was limited to 25 minutes. The choice of a 100-point continuous scale as opposed to a discrete 5-point ITU-R Absolute Category Scale (ACR) has advantages: expanded range, finer distinctions between ratings, and demonstrated prior efficacy [44].

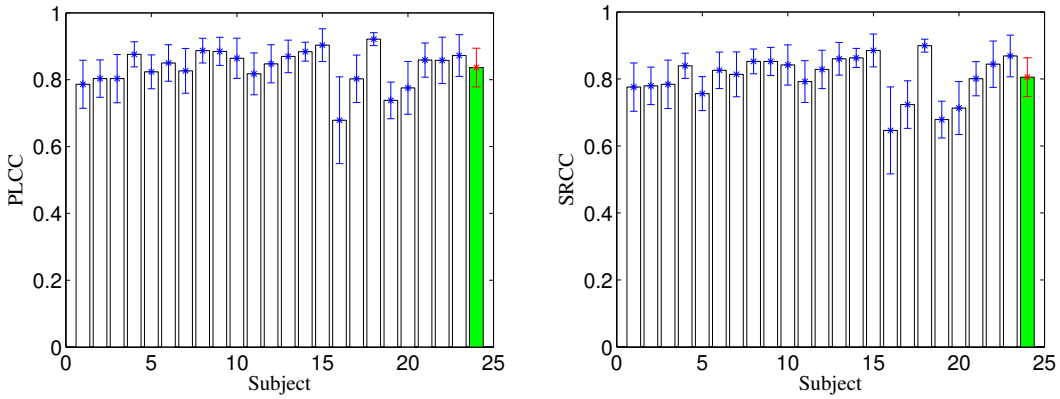
A common dilemma in every subjective video quality experiment is how much instruction should be given to the subjects. In practice, humans are often attracted by video content rather than quality variations. But to collect quality scores, certain instruction has to be given to the subjects in order to obtain their opinions on video quality. On the other hand, if too much instruction is given, the subjects may be over-educated to give "clean" but unrealistic scores. In our study, to give uniform instruction to all subjects, and to investigate the interactions between presentation quality and delay/stalling, we find it necessary to inform the subjects about what types of quality degradations they should expect to see. Other than that, no further specifications are given.

Since the break between successive test sessions is considerably short, alignment on the

subjective scores is not performed. In other words, raw subjective scores are used in the subsequent analysis. After the subjective user study, two outliers are removed based on the outlier removal scheme suggested in [32]. After outlier removal, Z-scores are linearly rescaled to lie in the range of [0, 100]. The final quality score for each individual image is computed as the average of rescaled Z-scores, namely the mean opinion score (MOS), from all valid subjects. The final quality score for each individual image is computed as the average of subjective scores, namely the mean opinion score (MOS), from all valid subjects. Considering the MOS as the "ground truth", the performance of individual subjects can be evaluated by calculating the correlation coefficient between individual subject ratings and MOS values for each image set, and then averaging the correlation coefficients of all image sets. The Pearson linear correlation coefficient (PLCC) and Spearman's rand-order correlation coefficient (SRCC) are employed as comparison criteria, whose range is from 0 to 1 and higher values indicate better performance. They can be computed for each subject and their values for all subject are depicted in Fig. 3.2. It can be seen that each individual subject performs well in terms of predicting MOSs. The average performance across all individual subjects is also given in the rightmost column in Fig. 3.2. This provides a general idea about the performance of an average subject. Therefore, we conclude that considerable agreement is observed among different subjects on the perceived quality of the test video sequences.

3.1.2 Subjective Data Analysis

One of the main objectives of this subjective experiment is to investigate whether the impact of the stalling events are independent of the video presentation quality. If the



(a) (b)

Figure 3.2: PLCC and SRCC between individual subject rating and MOS. Rightmost column: performance of an average subject.

answer is yes, then regardless of the video presentation quality, stallings will have the same impact on the overall QoE scores. Assuming an additive relationship between stalling and video presentation quality as in [23], we are expecting a near constant MOS drop across different video presentation quality when a stalling event occurs in the middle of the sequences.

Fig. 3.3 shows a scatter plot of the instantaneous quality of the freezing frame predicted by SSIMplus [58] and the MOS degradation for both initial delay and playback stalling. It can be observed that for the stalling at the same temporal instance and of the same duration, human subjects tend to give a higher penalty to the video with a higher instantaneous video presentation quality at the freezing frame. We further performed a statistical significance test as follows. Denoting the SSIMplus score of the initial buffered/stalling frame, and the MOS drop of the test video with initial buffering/stalling as random variables X_1/X_2 and Y_1/Y_2, we specify the null hypotheses H_1/H_2 as that X_1/X_2 is uncorrelated

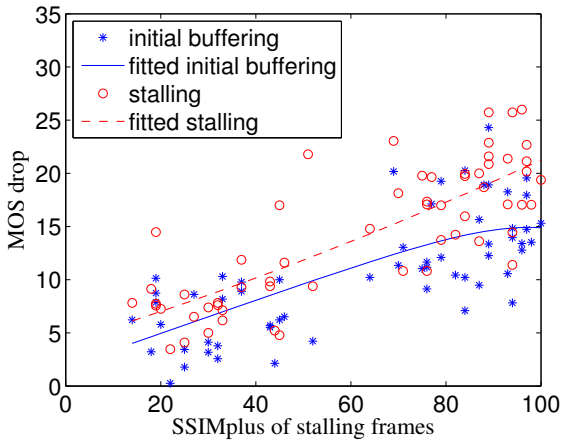


Figure 3.3: SSIMplus of stalling frames vs. MOS drop.

with Y_1/Y_2. The test statistic is $t = \frac{r\sqrt{N-2}}{1-r^2}$, where r and N are the correlation coefficient and the number of samples, respectively. The resulting test statistic is used to compute the P-values by referring to a t-distribution with $N-2$ degrees of freedom. Since the P-values (6.32x10^{-8} for initial buffering and 6.87x10^{-13} for stalling) are much smaller than the significance level 0.05, we reject the null hypotheses in favor of the alternatives. The results suggest that there is sufficient evidence at the 0.05 significance level to conclude that there is a linear relationship in the population between the SSIMplus score (estimation of the presentation quality) of the initial buffered/stalling frame and the QoE drop. This phenomenon was not observed in previous studies. One explanation may be that there is a higher viewer expectation when the video presentation quality is high, and thus the interruption caused by stalling make them feel more frustrated.

3.2 Adaptive Streaming Video Database

Even though the Waterloo SQoE-I database illustrates interesting relationship between the presentation video quality and impact of stalling events, it may not be an excellent resource to validate the performance of objective QoE models. The degradations of the presented video sequences are isolated. Combined degradations, like initial delay and compression, or initial delay and stalling, are not investigated. As in a realistic setting, combined degradations are not an exception, the results of this study cannot really be directly transferred. Furthermore, the influence of bitrate switching, which has been recognized as an important factor of QoE for adaptive streaming [66, 22], should also be investigated. Realizing the need for an adequate resource, we have endeavored to create the Waterloo Streaming QoE Database II (SQoE-II).

3.2.1 Video Database Construction and Subjective User Study

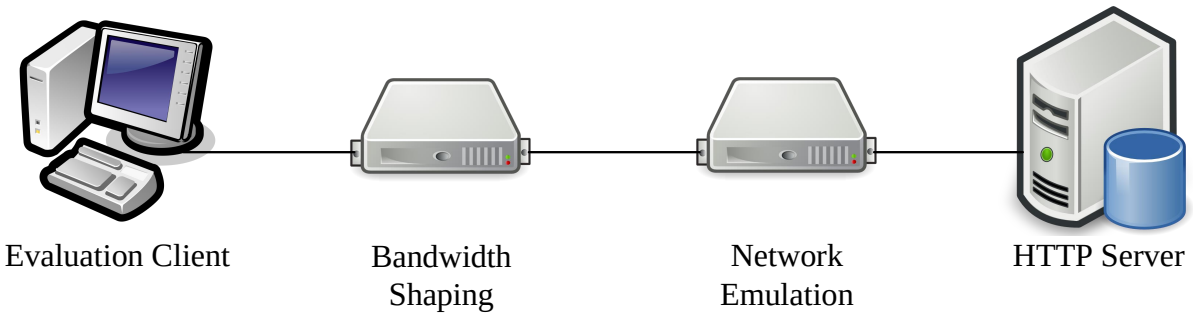


Figure 3.4: Experimental setup.

In order to generate meaningful and representative test videos, we conducted a set of DASH video streaming experiments, recorded the relevant streaming activities, and

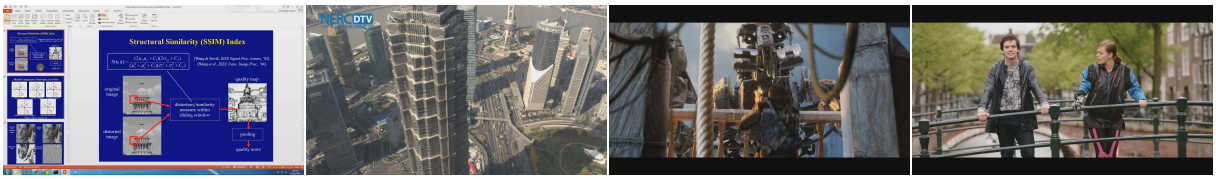
reconstructed the streaming session using video processing tools. We followed the recommendation in [74] and [50] to setup the testbed. The architecture of the testbed is depicted in Fig. 3.4 and consists of four modules: two computers (Ubuntu 14.04 LTS) with a 100Mbps direct network connection emulating a video client and server. DASH videos were pre-encoded and hosted on an Apache web server. The main components of this architecture were the bandwidth shaping and the network emulation nodes which were both based on Ubuntu utilities. The bandwidth shaping node controlled the maximum achievable bandwidth for the client with the Linux traffic control system (tc) and the hierarchical token bucket (htb) which is a classful queuing discipline (qdisc). The available bandwidth for the client was adjusted every second according to bandwidth traces. The video client, where adaptation algorithms were deployed, was a Google Chrome web browser for Linux (version 44) with V8 JavaScript engine while the video server was a simple HTTP server based on node.js (version 0.10.40). After each video streaming session, a log file was generated on the client device, including selected bitrates, duration of initial buffering, start time, and end time of each stalling event. According to the recorded logs, we reconstructed each streaming session by concatenating streamed bitrate representations, appending blank frames to the test video to simulate initial buffering, and inserting identical frames at the buffering time instance to simulate stalling event. The loading indicator (for both initial buffering and stalling) was implemented as a spinning wheel. We describe each module in the testbed in detail throughout this section.

Source Videos and Encoding Configuration: A video database of twenty pristine high-quality videos of size 1920×1080 were selected to cover diverse content, including humans, plants, natural scenes, architectures, screen content, and computer-synthesized

(a) BigBuckBunny (b) BirdOfPrey (c) Cheetah (d) CostaRica

(e) CSGO (f) FCB (g) FrozenBanff (h) Mtv

(i) PuppiesBath (j) RoastDuck (k) RushHour (l) Ski



(m) SlideEditing (n) TallBuildings (o) TearsOfSteel1 (p) TearsOfSteel2

(q) TrafficAndBuilding (r) Transformer (s) Valentines (t) ZapHighlight

Figure 3.5: Snapshot of sequences.

sceneries. RushHour, TallBuildings, and TrafficAndBuilding were from the SJTU 4K video dataset [69]. All videos have the length of 10 seconds [21]. The detailed specifications of those videos are listed in Table 3.2 and a screenshot from each video is included in Fig. 3.5. Spatial information (SI) and temporal information (TI) [33] that roughly reflect the specifications of video content are also given in Table 3.2. Apparently, the video sequences are of diverse spatio-temporal complexity and widely span the SI-TI space. Using aforementioned sequences as the source, each video was encoded into eleven representations as shown in Table 3.3 with x264 encoder to cover different quality levels. The choices of bitrate levels were based on the Netflix's recommendation [51] while representation eleven was appended to the original bitrate ladder to cover the high-quality representation suggested in the Apple's recommendation [3]. We segmented the test sequences with GPAC's MP4Box [38] with a segment length of 2 seconds for the following reasons. First, 2-second segments are widely used in the development of adaptation logics and is the most common segment size currently adopted by actual deployments. On the other hand, we aimed to design test videos in an efficient way such that they cover a diverse adaptation patterns in a limited time.

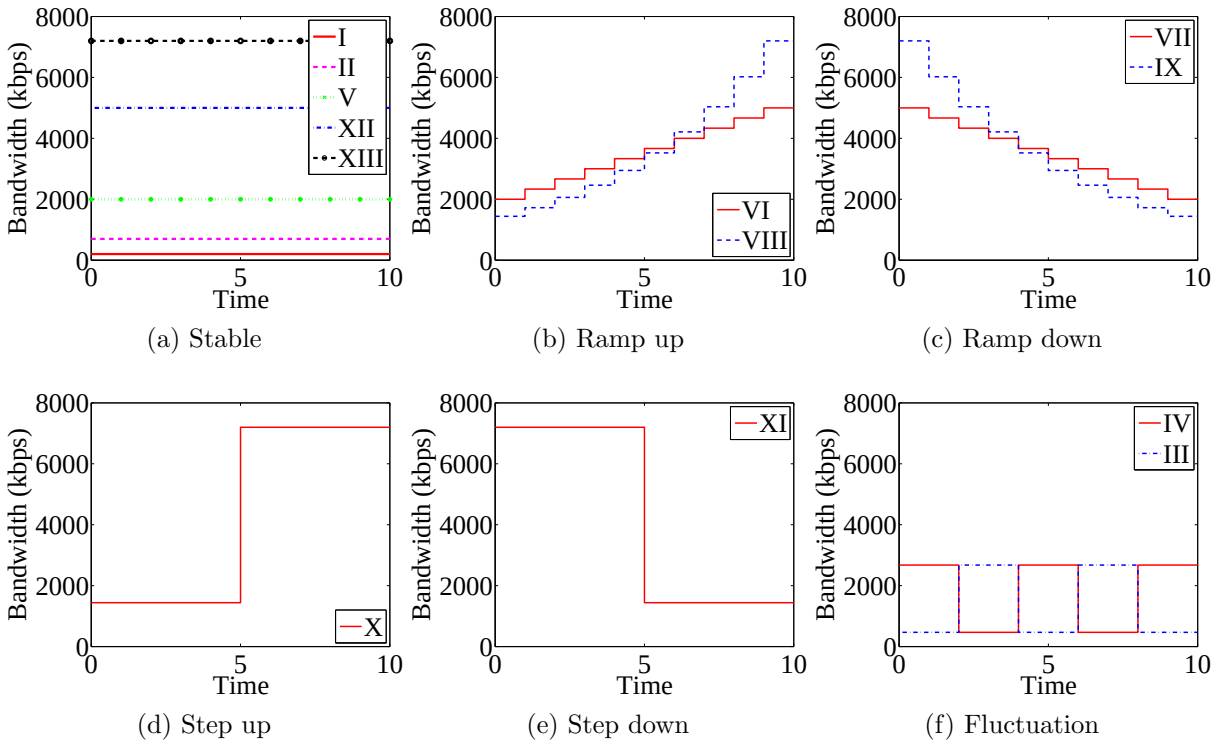
Bandwidth shaping: The delay of network simulator was set to 80ms corresponding to what can be observed within long-distance fixed line connections or reasonable mobile networks, and thus is representative for a broad range of application scenarios as suggested in [74]. We used 13 network traces shown in Fig. 3.6 that are wide-ranging and representative including stationary as well as different mobility scenarios, such as pedestrian, car, train, etc. The average bandwidth of the network traces varies between 200Kbps and 7.2Mbps covering all range of bitrates in the bitrate ladder.

Table 3.2: Spatial information (SI), temporal information (TI), frame rate (FPS), and description of reference videos

Name	FPS	SI	TI	Description
BigBuckBunny	30	96	97	Animation, high motion
BirdOfPrey	30	44	68	Natural scene, smooth motion
Cheetah	25	64	37	Animal, camera motion
CostaRica	25	45	52	Natural scene, smooth motion
CSGO	60	70	52	Game, average motion
FCB	30	80	46	Sports, average motion
FrozenBanff	24	100	88	Natural scene, smooth motion
Mtv	25	112	114	Human, average motion
PuppiesBath	24	35	45	Animal, smooth motion
RoastDuck	30	60	84	Food, smooth motion
RushHour	30	52	20	Human, smooth motion
Ski	30	61	82	Sport, high motion
SlideEditing	25	160	86	Screen content, smooth motion
TallBuildings	30	81	13	Architecture, static
TearsOfSteel1	24	53	66	Movie, smooth motion
TearsOfSteel2	24	56	11	Movie, static
TrafficAndBuilding	30	66	15	Architecture, static
Transformer	24	72	56	Movie, average motion
Valentines	24	40	52	Human, smooth motion
ZapHighlight	25	97	89	Animation, high motion

Table 3.3: MPEG-DASH representations for test sequence

Representation index	Resolution	Bitrate (kbps)
1	320×240	235
2	384×288	375
3	512×384	560
4	512×384	750
5	640×480	1050
6	720×480	1750
7	1280×720	2350
8	1280×720	3000
9	1920×1080	4300
10	1920×1080	5800
11	1920×1080	7000



(a) Stable (b) Ramp up (c) Ramp down

(d) Step up (e) Step down (f) Fluctuation

Figure 3.6: Bandwidth profiles used in the experiment. The profiles are indexed from the lowest to the highest average bandwidth.

ABR algorithms: We prototyped six bitrate adaptation algorithms in an open source dynamic adaptive streaming player called dash.js [10]. Our choice of platform is a pragmatic one because it is the reference open-source implementation for the MPEG-DASH standard based on the HTML5 specification and is actively supported by leading industry participants. The implementation details of the six bitrate adaptation algorithms are listed as follows:

1. Rate-based [10]: The rate-based adaptation algorithm, which is the default logic in the DASH standard, picks the maximum available bitrate which is less than throughput prediction using the arithmetic mean of past 5 chunks. The original algorithm starts with a constant bitrate if the viewing history is not available in the DOM storage. We set the initial bitrate to 1200Kbps.

2. Buffer-based [30]: We employ the function suggested by Huang *et al.* [30], where bitrate is chosen as a piecewise linear function of buffer occupancy. The algorithm always starts with the lowest bitrate till the buffer occupancy reaches a certain threshold called reservoir. Once reservoir is filled up, the algorithm allows to select a higher bitrate as the buffer occupancy increases till there is enough video segment in the buffer (upper reservoir) to absorb the variation caused by the varying capacity and by the finite chunk size, where the range from the lower to upper reservoir is defined as cushion. We set lower reservoir and cushion to be 2 and 5 seconds, respectively.

3. AIMD [40]: The algorithm proposed by Liu *et al.* picks the representation according to the bandwidth estimation using the previous downloaded chunk in a additive

increase multiplicative decrease manner. When the two thresholds for switching are not met, the algorithm keeps the selected bitrate.

4. ELASTIC [12]: This algorithm incorporates a PI-controller to maintain a constant duration of video in the buffer (5 seconds in the experiment). Since the bandwidth estimation module is not specified in the original implementation, we adopt the throughput prediction using harmonic mean of the past 5 chunks, because it is shown to be effective in previous studies [35].

5. QDASH [46]: QDASH picks an intermediate bitrate when there is a bandwidth drop to mitigate the negative impact of abrupt quality degradation. Without impacting the performance, we replace the proxy service for bandwidth estimation in the original implementation with the throughput prediction using harmonic mean of past 5 chunks for simplicity.

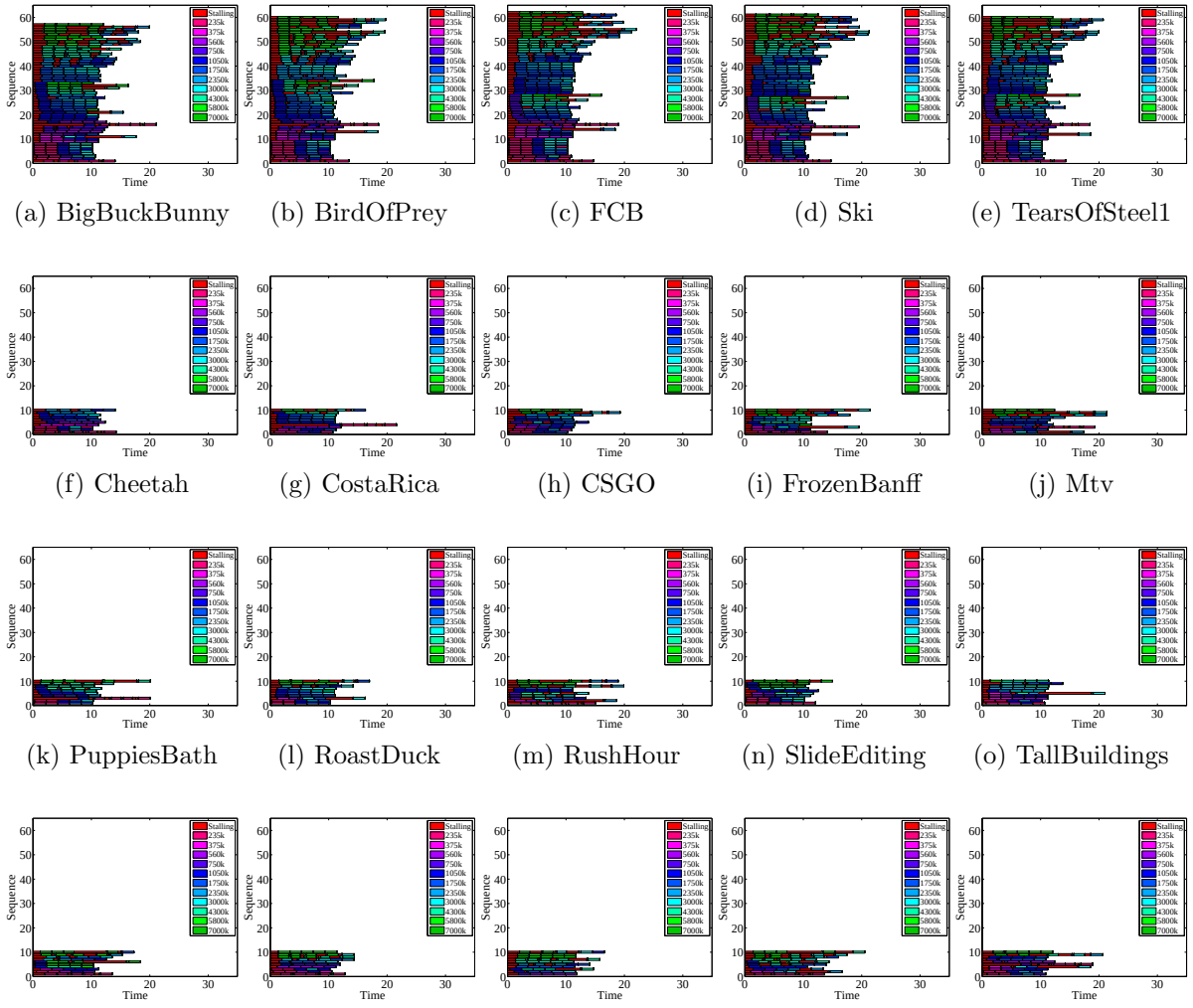
6. FESTIVE [35]: This rate-based algorithm balances both efficiency and stability, and incorporates fairness across players but that is not a concern of this paper. We assume there is no wait time between consecutive chunk downloads, and implement FESTIVE without the randomized chunk scheduling. Note that this does not negatively impact the player QoE. Specifically, FESTIVE calculates the efficiency score depending on the throughput prediction using harmonic mean of the past 5 chunks, as well as a stability score as a function of the bitrate switches in the past 5 chunks. The bitrate is chosen to the minimize stability score plus $\alpha = 12$ times efficiency score.

Since the selection of initial bitrate is not explicitly defined in AIMD, Elastic, QDASH, and FESTIVE, to provide a realistic simulation and to cover a diverse distortion pattern,

we add a random noise with standard deviation of 200Kbps to the initial bitrate in the actual trace as the selected initial bitrate.

In the end of the simulation, a total of 1,560 streaming sessions (20 source videos $\times$ 6 adaptation algorithms $\times$ 13 bandwidth profiles) are recorded. Around 25% of the streaming videos are found to be duplications of each other due to the intrinsic similarity between the adaptation algorithms, and thus are discarded from the subjective experiment to shorten its duration, resulting in 1,164 unique streaming videos. Due to the limited duration of the subjective experiment, we randomly select ten streaming sessions from the resulting streaming video pool for fifteen contents and reconstruct all the streaming sessions of the other five contents. In summary, the Waterloo SQoE-II database consists of twenty reference videos and 450 distorted videos, and of average duration thirteen seconds. The detailed profile of the streaming videos is illustrated in Fig. 3.7. Under the assumption that the video player's resolution does not change during video playback and the videos are always played at full-screen mode, all YUV frames are upsampled to 1920$\times$1080 and then encapsulated into MP4 containers in order to match the rendering device resolution.

We adopt the same subjective testing methodology and data processing procedure as in Section 3.1. A total of 34 naïve subjects, including nineteen males and fifteen females aged between 18 and 35, participate in the subjective test. For each subject, the whole study takes about three hours, which is divided into six sessions with five 7-minute breaks in-between. In order to minimize the influence of fatigue effect, the length of a session was limited to 25 minutes. Subsequently, 4 outliers are removed based on the outlier removal scheme suggested in [32], resulting in 30 valid subjects. After outlier removal, Z-scores are linearly rescaled to lie in the range of [0, 100]. The MOS for each individual video is



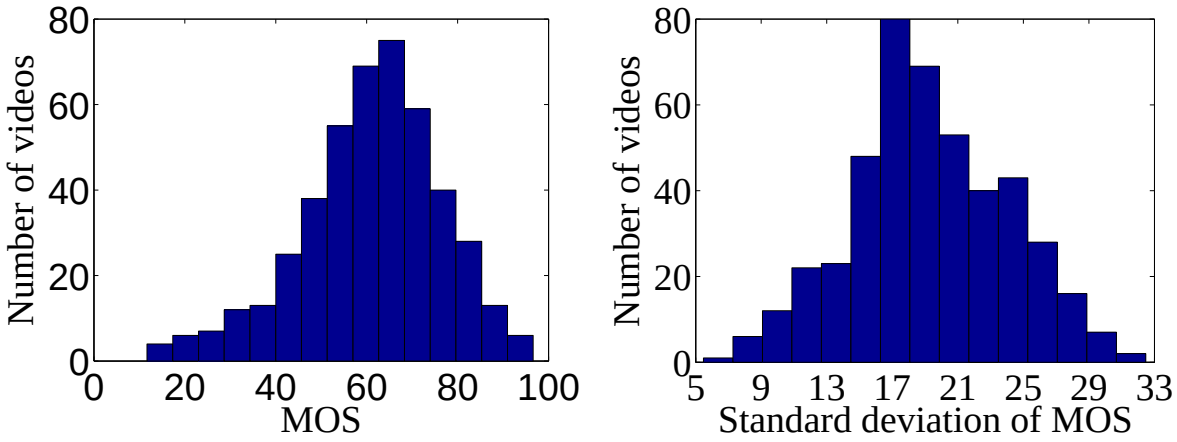
(a) BigBuckBunny (b) BirdOfPrey (c) FCB (d) Ski (e) TearsOfSteel1

(f) Cheetah (g) CostaRica (h) CSGO (i) FrozenBanff (j) Mtv

(k) PuppiesBath (l) RoastDuck (m) RushHour (n) SlideEditing (o) TallBuildings

(p) TearsOfSteel2 (q) Traffic&Building (r) Transformer (s) Valentines (t) ZapHighlight

Figure 3.7: Representation of selected sequences.



(a) MOS (b) Std. dev. MOS

Figure 3.8: Quality characteristic of Waterloo SQoE-II database.

computed as the average of rescaled Z-scores, from all valid subjects. Fig. 3.8 plots the MOS scores across distorted videos for the subjective study, and shows the corresponding histograms for the MOS and the associated standard deviation in order to demonstrate that the distorted videos span most of the quality range. The average standard deviation in the MOS was 19 across the 450 distorted videos. By comparison, however, subjects have a less degree of agreement in QoE for streaming videos with combined degradations than videos with isolated degradations in LIVEMVQA [49] and Waterloo SQoE-I database [16]. The result motivates the development of per-view QoE monitoring and optimization systems in the future.

3.2.2 Evaluation of ABR Algorithms

We use MOS of the six ABR algorithms described in the previous section to evaluate and compare their performance. The mean of MOS values across different content under

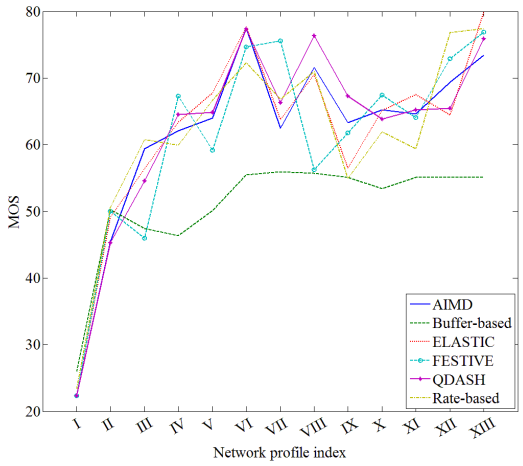


Figure 3.9: Performance of adaptation logic under testing network conditions.

thirteen network conditions for the ABR algorithms are summarized in Fig. 3.9. It is worth mentioning that this only provides a rough comparison of the relative performance of the ABR algorithms in the "startup phase". Besides, computational complexity is not a factor under consideration.

From the subjective test results, we have several observations. First, the video quality at which the content is streamed has a significantly higher impact on live content , *e.g.*, FCB, than on VoD content. In particular, none of the live video sequences of average bitrate lower than 800 kbps received a rating higher than 60. This conclusion is consistent with the previous study [14]. Second, buffer-based algorithm [30], which spent 60% of the time at bitrates lower than 1,000 kbps even under the best network condition in the experiment, provides the lowest QoE under most network conditions. Similarly, due to the conservative switching strategy where the player only switches to the next level and uses a lower rate of upward switches at higher representation levels, FESTIVE [35] (the algo-

rithm increase the bitrate at bitrate level k only after k chunks) performs poorly under the ramp up network condition VIII. This suggests that a consistently low video presentation quality is not tolerated by subjects. Third, FESTIVE [35] achieves the best performance under the ramp down network condition VII although it consumes the lowest bitrate among bandwidth-aware algorithms due to its multiplicative (0.85) factor on the estimated bandwidth. This conservative strategy helps tolerate the buffer fluctuation caused by variability in chunk size and reduces the likelihood of stalling, especially at high bitrates because a sudden bandwidth drop may results in longer stalling time at higher bitrates. Based on the two observations, we conclude that a QoE-driven ABR algorithm should adopt a stateful bitrate selection that performs aggressively at low bitrates and conservatively at high bitrates. While FESTIVE [35] takes the stateful approach, bitrate level is not a proper indicator of state because it does not generalize well to different size of bitrate ladder. Interestingly, previous studies [35] proved that such stateful design converges to a fair share of bandwidth if there are multiple competitors. Our results further emphasize the benefits of stateful design of ABR algorithms. Fourth, it can be observed from Fig. 3.9 that the rate-based algorithm [10] performs at least as good as other bandwidth-aware algorithms under network conditions I, II, and III while it performs poorly otherwise. This may be explained by the startup strategy. Since the rate-based algorithm [10] starts with a constant bitrate (1,200 kbps in our experiment) regardless of the network condition while the other bandwidth-aware algorithms start with bitrates around the initial bandwidth, the initial bitrates of the rate-based algorithm [10] is the highest among the bandwidth-aware algorithms under the first three network conditions and the lowest under other network conditions. The results suggest that the fast startup strategy that begins with low bi-

trates is not appreciated by the subjects. This phenomenon is also orally confirmed by the participants: about 40% of subjects reported that initial buffering events of duration less than 4 seconds is acceptable and the initial impression of video quality plays an important role in the QoE. Fifth, QDASH [46] that temporarily trades the buffer occupancy for high bitrates during bandwidth drop outperforms all other algorithms under the ramp down network condition XI, which confirms that smooth quality degradations are preferred over abrupt transitions [46]. From the algorithm design space point of view, both rate-based and buffer-based algorithms discard useful information, and thus result in suboptimal solution. Sixth, not a single algorithm provides the best perceptual quality under all network profiles. This suggests that there is still room for future improvement, and proper combination of the ideas used in different ABR algorithms has the potential to further improve the performance.

3.3 Summary

We have presented two subjective studies to understand human visual QoE of streaming video. The first subjective experiment reveals some interesting relationship between the impact of stalling and the instantaneous presentation quality. We evaluate the performance of ABR algorithms with the second streaming video database and provide useful insights for future improvement.

Chapter 4

Objective Quality-of-Experience Model of Streaming Videos

In this chapter, we aim to tackle the problem of objective QoE assessment for streaming videos. In order to validate the proposed QoE model, we carried out by far the most comprehensive evaluation of objective QoE models on the two subject-rated databases. Finally, we shed light on the practical real-time QoE monitoring frameworks throughout the delivery chain.

4.1 A Quality-of-Experience Index for Streaming Video

Motivated by the observation and analysis provided in Section 3.1, we develop a unified QoE prediction model named Streaming QoE Index (SQI) by incorporating the video presentation quality and the impact of initial buffering and stalling events. In particular,

we consider QoE as a combined experience of video presentation quality, stalling experience and their interaction.

4.1.1 Video Presentation Quality

For each frame in the streaming video, its instantaneous video presentation quality P_n can be estimated at the server side by a frame-level VQA model before transmission

$$P_n = V(X_n, R_n), \tag{4.1}$$

where X_n and R_n are the n-th frame of the streaming video and pristine quality video, and $V(\cdot)$ is a full reference VQA operator. The computed quality score $V(X_n, R_n)$ can either be embedded into the manifest file that describes the specifications of the video, or carried in the metadata of the video container. Currently, the development of the next-generation ISO base media file format that incorporates time-varying video quality metric is ongoing [31]. The manifest or metadata file is transmitted to the client side such that its information is available to the client. In commonly used streaming protocols such as MPEG-DASH, the partially decoded frame will not be sent for rendering, and thus viewers will see the last successfully decoded frame during the stalling interval. Thus, for a stalling moment n in the interruption period $[i, j]$, the video presentation quality at the instance, P_n, is the same as the quality of the last decoded frame

$$P_n = P_{i-1}. \tag{4.2}$$

4.1.2 Stalling Experience Quantification

To simplify the formulation, we assume the influence of each stalling event is independent and additive. As such, we can analyze each stalling event separately and compute the overall effect by aggregating them. Note that each stalling event divides the streaming session time line into three non-overlapping intervals, i.e., the time intervals before the stalling, during the stalling, and after the stalling. We will discuss the three intervals separately because the impact of the stalling event on each of the intervals are different.

First, we assign zero penalty to the frames before the stalling occurs when people have not experienced any interruption. Second, as a playback stalling starts, the level of dissatisfaction increases as the stalling goes on till playback resumes. The study on the impact of waiting time on user experience in queuing services [37] has a long history from both an economic and a psychological perspective, and has been recently extended to quantify the relationship between QoE and QoS in adaptive streaming [19]. The exponential decay function has been successfully used in previous studies [19][29][28]. The use of exponential decay assumes an existence of QoE loss saturation to the number and length of stalling, and low tolerance to jitters comparing to the other commonly used utility function such as logarithm and sigmoid. Here we approximate the QoE loss due to a stalling event with an exponential decay function similar to [19][29][28]. Third, QoE also depends on a behavioural hysteresis "after effect" [64]. In particular, a previous unpleasant viewing experience caused by a stalling event tends to penalize the QoE in the future and thus affects the overall QoE. The extent of dissatisfaction starts to fade out at the moment of playback recovery because observers start to forget the annoyance. To model the decline of memory retention of the buffering event, we employ the Hermann Ebbinghaus forgetting

curve [17]

$$M = \exp\left\{-\frac{t}{T}\right\}, \tag{4.3}$$

where M is the memory retention, T is the relative strength of memory, and t is the time instance.

Assume that the k-th stalling event locates at $[i_k,\, i_k + l_k]$, where l_k is the length of stall, a piecewise model is constructed to estimate the impact of each stalling event on the QoE

$$S^k(t) = \begin{cases} P_{i_k-1}\left(-1 + \exp\left\{-\left(\frac{tf - i_k}{T_0}\right)\right\}\right) & \frac{i_k}{f} \le t \le \frac{i_k+l_k}{f} \\ P_{i_k-1}\left(-1 + \exp\left\{-\left(\frac{l_k}{T_0}\right)\right\}\right) & \\ \cdot\left(\exp\left\{-\left(\frac{tf - i_k - l_k}{T_1}\right)\right\}\right) & t > \frac{i_k+l_k}{f} \\ 0 & otherwise \end{cases} \tag{4.4}$$

where f is the frame rate in frames/second, and T_0, T_1 and $S^k(t)$ represent the rate of dissatisfaction, the relative strength of memory and the experience of the k-th stalling event at time t, respectively. P_{i_k-1}, the scaling coefficient of the decay function, has two functions: 1) it reflects the viewer expectation to the future video presentation quality, and 2) it normalizes the stalling effect to the same scale of VQA kernel. This formulation is qualitatively consistent with the relationship between the two QoE factors discussed in the previous section. In addition, since the impact of initial buffering and stalling are different, we have two sets of parameters: $\{T_0^{init}, T_1^{init}\}$ for initial delay and $\{T_0, T_1\}$ for other playback stallings, respectively. We also assume the initial expectation P_0 is a constant. In this way, the initial buffering time is proportional to the cumulated experience loss.

The instant QoE drop due to stalling events is computed by aggregating the QoE drop

caused by each stalling event and is given by

$$S(t) = \sum_{k=1}^{N} S^k(t), \tag{4.5}$$

where N is the total number of stalling events.

An important fact we have learned from the previous subjective study [49] is that the frequency of stalling negatively correlates with QoE for a streaming video of constant quality, sufficient length, and a fixed total length of stalling L. Although not explicitly defined in the expression, it can be shown that the effect of stalling frequency can be captured by the proposed model with a deliberate parameter selection. To see that, we first adopt the aforementioned test condition in [49] and assume $P_n = C$, where C is a positive constant. Then, the end-of-process QoE of the proposed model is fully determined by experience loss of stalling, which becomes a function of stalling frequency only. When the total length of stalling L is fixed and assume equal length of each individual stall, then the length of each stall is L/N, and the stalling frequency is inverse proportional to the total number of stalls N. Thus, we only need to check whether the cumulated QoE drop over all time

$$G(N) = \int_{-\infty}^{\infty} S(t)dt, \text{ for } l_k = \frac{L}{N}, k = 1, 2, ..., N \tag{4.6}$$

is monotonically decreasing with respect to N. By substituting Eqs. (4.4) and (4.5) into (4.6), we can simplify the expression as

$$G(N) = C\,(T_1 - T_0)\left\{N \exp\left[-\left(\frac{L}{NT_0}\right)\right] - N\right\} - CL \quad \text{for } N \geq 1, T_0 > 0, T_1 > 0, L > 0. \tag{4.7}$$

Let $g(x) = x \exp\left\{-\left(\frac{L}{xT_0}\right)\right\} - x$, it is not hard to verify $\frac{dg(x)}{dx} < 0, \forall x \geq 1$. Therefore, the model is able to implicitly account for the effect of stalling frequency as long as $T_1 > T_0$.

In addition, we have also learned from previous subjective study [29] that the impact of stalling tends to saturate with the increase of the number of stalling events at a constant quality setting. Interestingly, with the independent and additive assumption, SQI is still able to predict that the overall QoE has an exponential-like response for each addition stalling event. To understand this, let us denote the video presentation quality of each frame/segment, the length of static video in seconds, the duration of each stalling events, the number of stalling events, and the overall QoE by P_n, T, T_s, N, and Q, respectively. In [29], the authors performed their subjective study with a constant quality setting, *i.e.*, $P_n = P$. According to Eq. (4.2), the video presentation quality that caused by the stalling events changes from $P_n = P, \forall n \in [0, T]$ to $P_n = P, \forall n \in [0, T + NT_s]$. According to Eq. (4.5), the overall stalling experience is $NS^k(T_s), \forall k \in [1, N]$. Thus, the overall QoE can be represented as $Q = \frac{(T+NT_s)P+NS_k(T_s)}{T+NT_s}$. We plot Q with respect to N on a 5-point absolute category rating (ACR) scale in Fig. 4.1, where it can be observed that the influence of each additional stalling event follows an exponential-like decreasing pattern in SQI.

In real-world applications, to measure the impact of stalling at individual frames, we convert the continuous function in Eq. (4.5) into its discrete form by sampling the function at each discrete time instance n:

$$S_n = S\left(\frac{n}{f}\right). \tag{4.8}$$

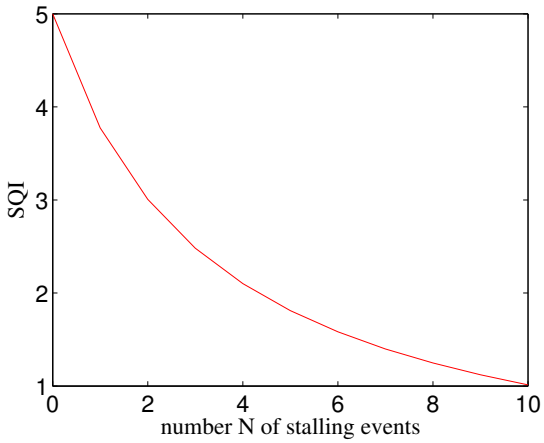


Figure 4.1: SQI at different number of stalling events.

4.1.3 Overall QoE

The instantaneous QoE at each time unit n in the streaming session can be represented as the aggregation of the two channels

$$Q_n = P_n + S_n. \tag{4.9}$$

In practice, one usually requires a single end-of-process QoE measure. We use the mean value of the predicted QoE over the whole playback duration to evaluate the overall QoE. To reduce the memory usage, the end-of-process QoE can be computed in a moving average fashion

$$A_n = \frac{(n-1)A_{n-1} + Q_n}{n}, \tag{4.10}$$

where A_n is the cumulative QoE up to the n-th time instance in the streaming session. An example of each channel and the final output of the model is illustrated in Fig. 4.2.

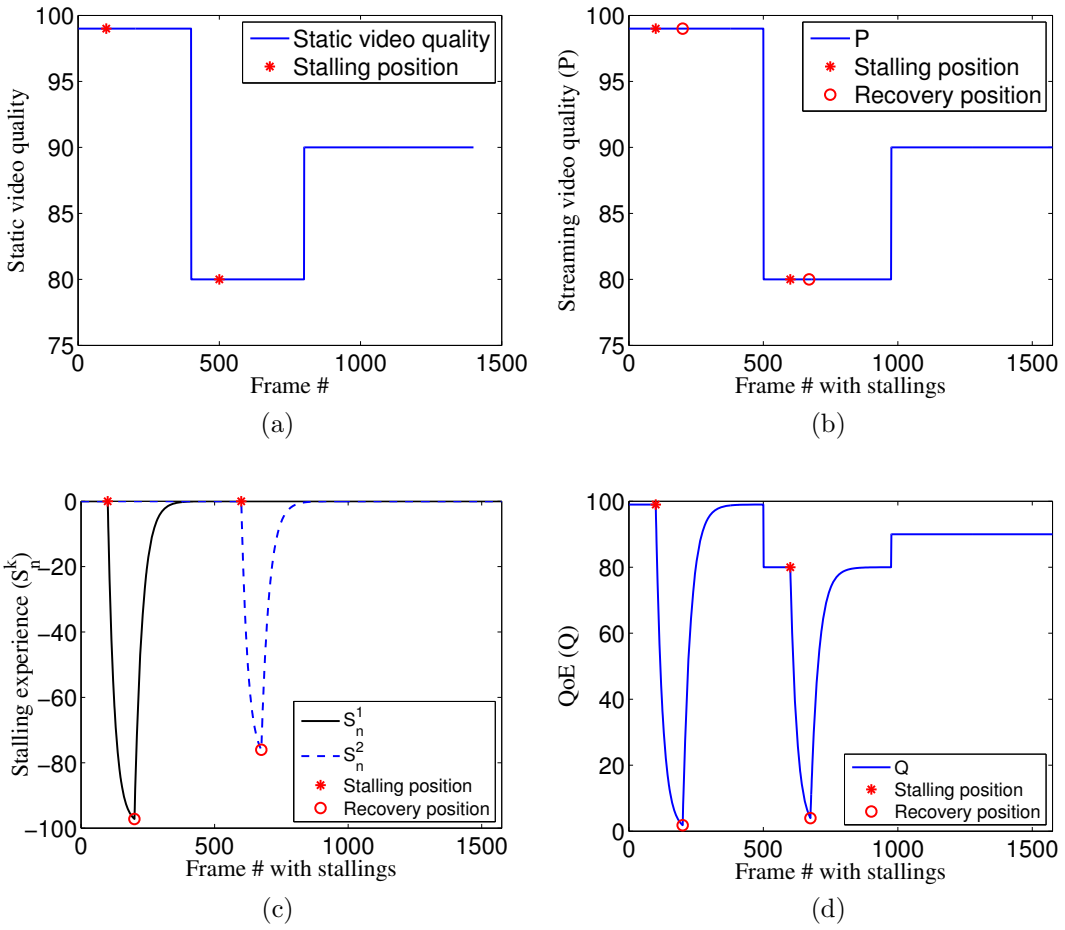


Figure 4.2: An illustrative example of and channel responses at each frame. (a) video presentation quality of the static video at each frame. '*' indicates the position of stalling. (b) video presentation quality of the streaming video during playback at each frame. '*' indicates the position of stalling and 'o' indicates the position of recovery. (c) QoE drop due to each stalling events at each frame. The solid curve shows the QoE drop due to initial buffering and the dashed curve shows the QoE drop due to playback stalling. (d) Overall QoE at each time instance during playback.

Table 4.1: SQI parameters.

Parameter	Description
T_0	rate of dissatisfaction in stalling event
T_1	strength of memory in stalling event
T_0^{init}	rate of dissatisfaction in initial buffering event
T_1^{init}	strength of memory in initial buffering event
P_0	expectation on initial quality of the video

4.1.4 Implementation details

Throughout the thesis, the proposed SQI uses the following parameter settings: $T_0^{init} = 2$, $T_1^{init} = 0.5$, $T_0 = 1$, $T_1 = 1.2$ and $P_0 = 0.8 \cdot |(V(\cdot)|$, where $|V(\cdot)|$ is the dynamic range of adopted VQA kernel, *e.g.* PSNR ranges from 0 to infinity (in the actual computation, we set the range of PSNR to 0-50); SSIM and MS-SSIM range from -1 to 1; and SSIMplus ranges from 0 to 100. These values are somewhat arbitrary, but we find that in our current experiments, the performance of the SQI is fairly insensitive to variations of T_0^{init}, T_1^{init}, T_0 and T_1 at least within an order of magnitude of the parameter values. P_0 is rather insensitive from $0.5|(V(\cdot)|$ (Xue's [83] selection) to $|(V(\cdot)|$. The parameters are summarized in the Table 4.1. Note that the initial buffering parameters do not have to satisfy the stalling frequency because it cannot occur more than once in one session. In real-world applications, the proposed scheme may include two step computations on the client side. First, stalling events are detected in the video player. A straightforward way to detect stalling events is to inspect the player progress every x milliseconds, *e.g.* 50. If the player has not advanced as much as it is expected to, then we can infer a stalling has occurred. By taking the difference between the expected progress and actual progress, the duration and frequency of stalling can be measured reliably. In the second step, which is

only necessary in the applications that require an end-of-process score, is the computation of the QoE cumulation. Both steps demand minimum computation and can be updated in real time. Moreover, the instantaneous QoE prediction is a valuable property for many applications such as live streaming quality monitoring and adaptive streaming decision making.

4.2 Performance of Existing Objective QoE Models

4.2.1 Progressive Streaming Video Database

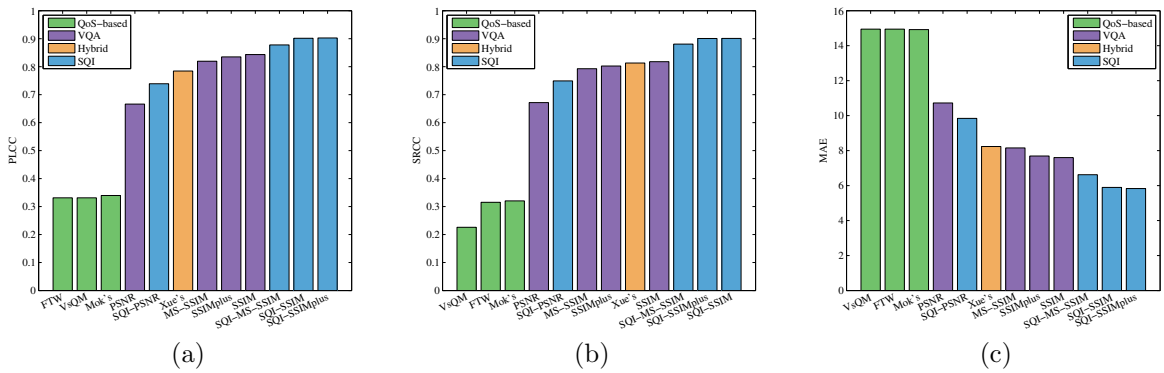
Using the Waterloo SQoE-I database, we test the performance of four existing VQA models, including PSNR, SSIM [78], MS-SSIM [80] and SSIMplus [58] and four state-of-the-art QoE models [47][61][28][83]. The implementations for the VQA models are obtained from the original authors and we implement four QoE models since they are not publicly available. For the purpose of fairness, all models are tested using their default parameter settings. In order to compare the performance of VQA and stalling-based QoE models, the quality of video without stalling are estimated by VQA and the result is applied to the same video with stalling events. For the hybrid model in [83], the model parameter c is not given in the original paper. We set $c = 0.05$ such that the model achieves its optimal performance on the current database. A comparison of the four QoE models is shown in Table 4.2. Three criteria are employed for performance evaluation by comparing MOS and objective QoE. Some of the criteria are included in previous tests carried out by the video quality experts group [75]. Other criteria are adopted in previous study [67]. These evaluation criteria are:

Table 4.2: Comparison of the existing QoE methods.

QoE models	Stalling		Presentation quality	
	Regression function	Influencing factors	Regression function	Influencing factors
FTW [15]	exponential	stalling length, # of stalling	N/A	N/A
Mok's [40]	linear	stalling length, stalling frequency, initial buffering length	N/A	N/A
VsQM [17]	exponential	average stalling length per segment, # of stalling per segment, period per segment	N/A	N/A
Xue's [21]	logarithmic	stalling length, # of stalling, bit count of the stalling segment	linear	QP

1) PLCC after a nonlinear modified logistic mapping between the subjective and objective scores [67]; 2) SRCC; 3) Mean absolute error (MAE) after the non-linear mapping. Among the above metrics, PLCC and MAE are adopted to evaluate prediction accuracy, and SRCC is employed to assess prediction monotonicity [75]. A better objective VQA measure should have higher PLCC and SRCC while lower MAE values. Fig. 4.3 summarizes the evaluation results, which is somewhat disappointing because state-of-the-art QoE models do not seem to provide adequate predictions of perceived quality of streaming videos. Even the model with the best performance is only moderately correlated with subjective scores. These test results also provide some useful insights regarding the general approaches used in QoE models. First, the hybrid model [83] significantly outperforms QoS-QoE correlation models. This suggests that the importance of video presentation quality in QoE should not be underestimated. Second, even though modern VQA models cannot capture the experience loss of stalling, most of them performs reasonably well on the Waterloo SQoE-I database. These observations suggest a hybrid model that equips VQA methods as the video quality predictor would be more promising in QoE estimation.

We validate SQI model using the Waterloo SQoE-I database described in Section 3.1



(a) (b) (c)

Figure 4.3: PLCC, SRCC, and MAE of QoE models on the Waterloo SQoE-I database.

and compare its performance against eight existing objective QoE models. Among the eight QoE models, four VQA algorithms including PSNR, SSIM [78], MS-SSIM [80] and SSIMplus [58], are employed as the frame-level video presentation quality measures. They also provide useful baseline comparisons. PLCC, SRCC and MAE are calculated to evaluate the performance of all QoE models. The performance comparison results are provided in Fig. 4.3. It can be seen that the proposed method delivers the best performance in predicting subjective QoE on the Waterloo SQoE-I database with both compression and frame-freeze impairment.

Fig. 4.4 shows the scatter plots of the MOS prediction results for each QoE model. The existing QoE models, presentation VQA quality with and without incorporating the proposed methods are listed in the first, second and third columns, respectively. We have two observations here. First, the proposed SQI models significantly outperform their baseline presentation VQA models. It is obvious that a higher compactness in the scatter plots is achieved by applying the proposed model, which adds proper penalties for initial buffering and stalling in addition to the presentation quality impairment. Second, the best

Table 4.3: Statistical significance matrix based on F-statistics on the Waterloo SQoE-I database. A symbol "1" means that the performance of the row model is statistically better than that of the column model, a symbol "0" means that the row model is statistically worse, a symbol "-" means that the row and column models are statistically indistinguishable.

	FTW [28]	Mok's [47]	VsQM [61]	Xue's [83]	PSNR	SSIM [78]	MS-SSIM [80]	SSIMplus [58]	SQI-PSNR	SQI-SSIM	SQI-MS-SSIM	SQI-SSIMplus
FTW[28]	-	-	-	0	0	0	0	0	0	0	0	0
Mok's[47]	-	-	-	0	0	0	0	0	0	0	0	0
VsQM[61]	-	-	-	0	0	0	0	0	0	0	0	0
Xue's [83]	1	1	1	-	1	-	-	-	1	0	0	0
PSNR	1	1	1	0	-	0	0	0	-	0	0	0
SSIM [78]	1	1	1	-	1	-	-	-	1	0	-	0
MS-SSIM [80]	1	1	1	-	1	-	-	-	1	0	0	0
SSIMplus [58]	1	1	1	-	1	-	-	-	1	0	-	0
SQI-PSNR	1	1	1	0	-	0	0	0	-	0	0	0
SQI-SSIM	1	1	1	1	1	1	1	1	1	-	-	-
SQI-MS-SSIM	1	1	1	1	1	-	1	-	1	-	-	-
SQI-SSIMplus	1	1	1	1	1	1	1	1	1	-	-	-

performance is obtained by combining the proposed method with the SSIMplus [58] VQA model.

To ascertain that the improvement of the proposed model is statistically significant, we carry out a statistical significance analysis by following the approach introduced in [67]. First, a nonlinear regression function is applied to map the objective quality scores to predict the subjective scores. We observe that the prediction residuals all have zero-mean, and thus the model with lower variance is generally considered better than the one with higher variance. We conduct a hypothesis testing using F-statistics. Since the number of samples exceeds 50, the Gaussian assumption of the residuals approximately hold based on the central limit theorem [48]. The test statistic is the ratio of variances. The null hypothesis is that the prediction residuals from one quality model come from the same distribution and are statistically indistinguishable (with 95% confidence) from the residuals from another model. After comparing every possible pairs of objective models,

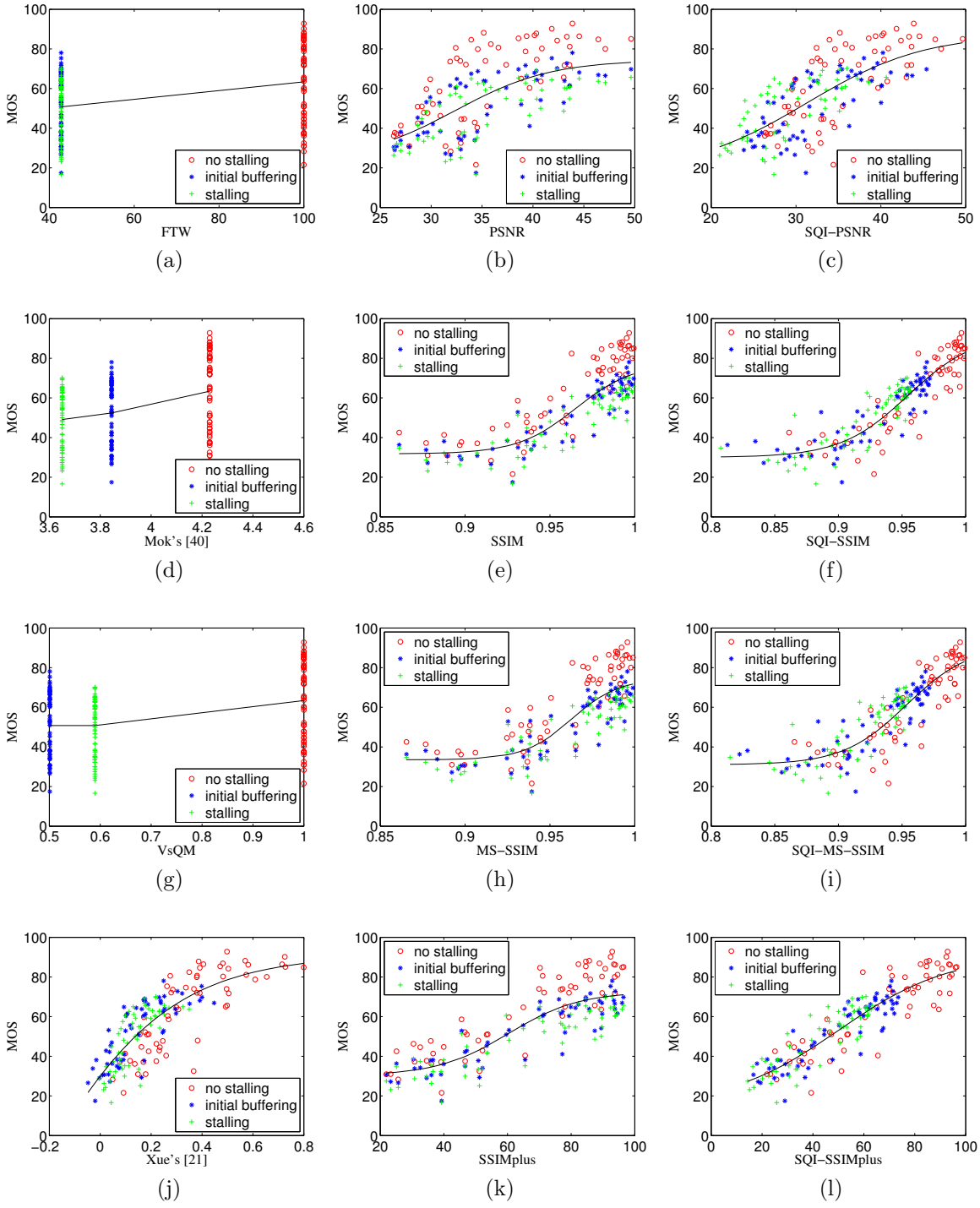


Figure 4.4: Predicted QoE vs. MOS.

the results are summarized in Table 4.3, where a symbol '1' means the row model performs significantly better than the column model, a symbol '0' means the opposite, and a symbol '-' indicates that the row and column models are statistically indistinguishable. It can be observed that most existing QoE models are statistically indistinguishable from each other, while the proposed model is statistically better than all other methods on the Waterloo SQoE-I database.

It can be observed from the experiments that the QoS-based QoE models [28][47][61] do not perform well on the database. The major reason is that QoS-based models (i.e., FTW [28], Mok's [47], and VsQM [61]), do not take the presentation quality of the videos into consideration except for their bitrates. A common "mistake" is to equate bitrate with quality, or assume a constant bitrate implies a constant presentation quality. This is highly problematic because videos coded at the same bitrate but of different content could have drastically different presentation quality. This is often the most dominant QoE factor, and in many cases all other factors (such as stalling) become only secondary. Indeed, this is quite apparent from our test results, where even PSNR, a very crude presentation quality measure that does not take into account any initial buffering or stalling at all, performs significantly better than QoS-based methods that ignore presentation quality. By contrast, the proposed method not only builds upon the most advanced presentation quality model (*e.g.*, SSIMplus, which has been shown to be much better than PSNR and other VQA measures), but moves one step further by capturing the interactions between video presentation quality and the impact of stalling.

4.2.2 Adaptive Streaming Video Database

4.2.3 Video Quality Assessment Models

Table 4.4: Performance comparison of VQA models on HAS video QoE database

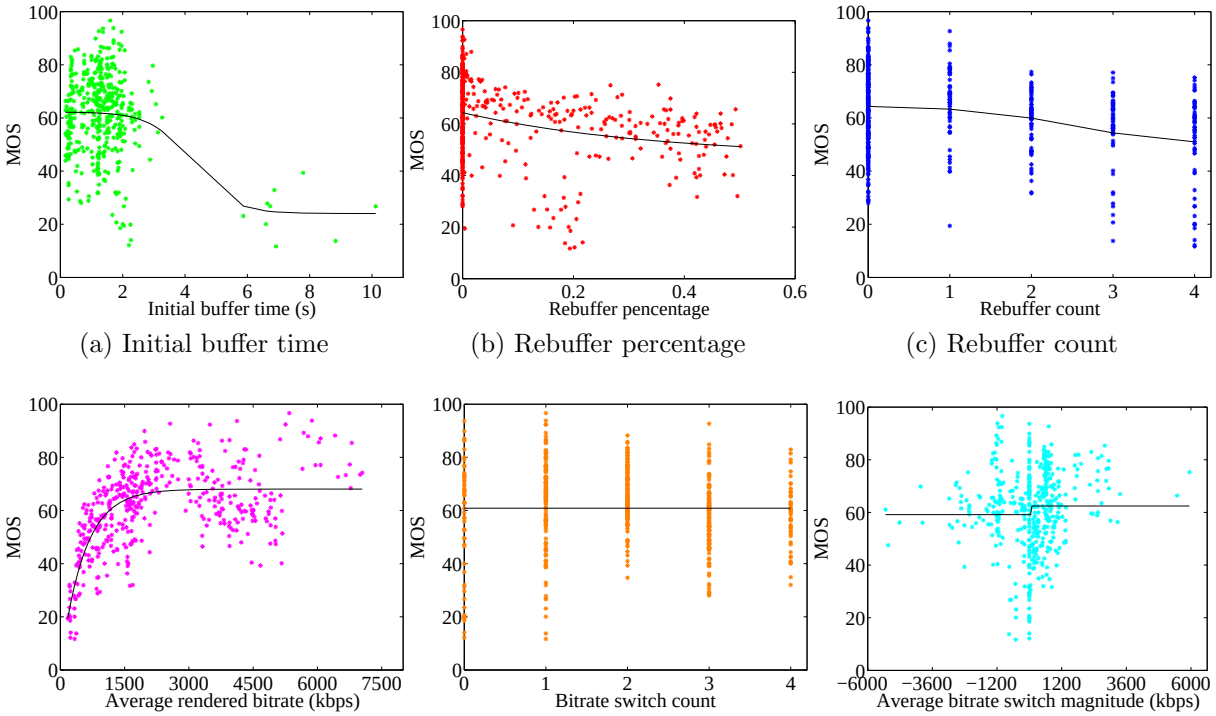
VQA model	D_A		D_B	
	PLCC	SRCC	PLCC	SRCC
PSNR	0.6767	0.6676	0.5368	0.4606
SSIM[78]	0.6157	0.6013	0.5162	0.4396
MS-SSIM[80]	0.7454	0.7438	0.6060	0.5217
SSIMplus[58]	0.8202	**0.8298**	0.6519	0.5617
VQM[55]	**0.8246**	0.8192	0.6716	**0.5650**
STRRED[70]	0.6766	0.6843	0.5453	0.4699
VMAF[39]	0.7988	0.7977	**0.6940**	0.5613
VIIDEO [45]	0.5046	0.4388	0.4781	0.3506

Modern video quality assessment (VQA) algorithms tackle the QoE problem by measuring the signal fidelity of a test video with respect to its pristine version. However, most VQA models do not consider the impact of playback interruption. Since VQA models serve as the major tools to measure the QoE of offline videos, it is imperative to understand whether they can be applied to streaming videos. In this regard, we evaluate a wide variety of VQA algorithms including PSNR, SSIM [78], MS-SSIM [80], STRRED [70], VQM [55], VMAF [39], SSIMplus [58], and VIIDEO [45] against human subjective scores on two datasets to test their generalizability on streaming videos, where dataset D_A includes the videos without stalling and dataset D_B contains all 450 streaming videos. The implementations of the VQA models are obtained from the original authors. Notice that we can do this as we will show later, the effect of initial buffering is insignificant in Section 4.2.4. Two criteria are employed for performance evaluation by comparing MOS and

objective QoE according to the previous study [67]: 1) PLCC after a nonlinear modified logistic mapping between the subjective and objective scores; 2) Spearman's rand-order correlation coefficient (SRCC). Since none of the full-reference VQA algorithms supports cross-resolution video quality evaluation except for SSIMplus, we up-sampled all representation to 1920×1080 and then apply the VQA on the up-sampled videos because it is the size of display in the subjective experiment. Table 4.4 summarizes the evaluation results. We have three observations from the experiment results. First, from the improvement of MS-SSIM and SSIMplus upon SSIM, we may conclude that multi-scale approach performs better against variations in resolution suggesting future refinements of VQA algorithms. Second, VIIDEO is the weakest among all VQA algorithms such that there remains significant room for improvement of no-reference VQA algorithms. Third, by comparing the performance of VQA algorithms on the two datasets, we conclude that the existing VQA algorithms are good at what they are designed for, but falls short of measuring QoE in the presence of stalling. Thus, a more general QoE model is required.

4.2.4 Industrial Standard QoE Models

DASH industry forum proposed a standard for client-side QoE media metrics [11]. As the standard metrics are widely used to assess the performance of ABR algorithms, it is critical to systematically investigate their performance. This knowledge can help providers to better invest their network and server resources toward optimizing the quality metrics. In this section, we evaluate five industry-standard QoE metrics [11], along with the average magnitude of switches that is also recognized as a major influencing factor of QoE [66]. We summarize the metrics below.



(a) Initial buffer time (b) Rebuffer percentage (c) Rebuffer count

(d) Average rendered bitrate (e) Bitrate switch count (f) Average bitrate switch magnitude

Figure 4.5: Qualitative relationships between six quality features and MOS.

1. Initial buffer time (T_i): Measured in seconds, this metric represents the duration from the player initiates a connection to a video server till the time that sufficient player video buffer has filled up and the player starts rendering video frames.

2. Rebuffer percentage (P_r): This metric is the fraction of the total session time (i.e., playing plus rebuffer time) spent in buffering. This is an aggregate metric that can capture periods of long video "freeze" observed by a user. It is computed as $\frac{\sum_i \text{ duration of rebuffer event } i}{\text{session duration}}$.

3. Rebuffer count (C_r): Rebuffer percentage does not capture the frequency of induced interruptions observed by a user. For example, a video session that experiences "video stuttering" where each interruption is small but the total number of interruptions is high, may not have a high buffering ratio, but may be just as annoying to a user.

4. Average rendered bitrate ($\overline{B}$): Measured in kilobytes per second, this metric is the most widely used video presentation quality measure in streaming applications. It is the average of the bitrates played weighted by the duration each bitrate is played.

5. Bitrate switch count (C_s): A single video session can have multiple bitrates played in HAS. Number of switches is usually used to quantify the flicker effects introduced by the quality variation. Several studies have argued that the

6. Average bitrate switch magnitude ($\overline{B}_s$): Measured in kilobytes per switch, this metric was also identified as an influencing factor of flicker effect. Conventional wisdom dictates that people prefer multiple switches with smaller bitrate differences to abrupt quality variation. It is computed as $\frac{\sum_{i=2}^{n} |\text{bitrate}_i - \text{bitrate}_{i-1}|}{\#\text{ of switches}}$, where n is the number of segments.

Fig. 4.5 shows the scatter plots of the six aforementioned quality metrics versus MOS. We evaluate the performance of each metrics using SRCC and summarize the result in Table 4.5. Fig. 4.5 shows that average rendered bitrate, rebuffer percentage, and rebuffer count have an monotonic relationship with MOS on average. While average rendered bitrate has the strongest correlation to MOS, it exhibits a strong nonlinear relationship with respect to MOS as shown in Fig. 4.5(a). In particular, bitrates in the range of 2,500 kbps to 7,200 kbps yield a very similar QoE. Furthermore, the seemingly well correlation between bitrate and quality would not hold true when video sequences encoded from various codecs and implementations are mixed together. Thus, existing video delivery optimization frameworks that always strive for higher bitrate in all ranges not only result in inefficient use of network, but also do not necessarily provide a better QoE. On the other hand, the two second-order statistics of bitrate - bitrate switch count and average bitrate switch magnitude - have relatively little impact to MOS. The impact of initial buffer time is the least significant. In addition, despite the general trend of MOS with respect to these quality metrics, none of the metric is sufficient to predict QoE accurately. In particular, initial buffer time, rebuffer percentage, rebuffer count, bitrate switch count, and average bitrate switch magnitude have very poor correlation with MOS. Even for the best metric average rendered bitrate, the difference in MOS given the bitrate could be as large as 50. Therefore, it is difficult to compare the performance of ABR algorithms and optimization frameworks with the statistics of isolated metrics, which unfortunately remains as the major validation approach. Moreover, we augment the correlation analysis with ANalysis Of Variance (ANOVA) on the MOS data to reveal the statistical significance of each metric on MOS, where the significance level p-value is set to 0.05. We choose bin sizes that

Table 4.5: SRCC between standard quality metrics and MOS

Quality metric	SRCC
Initial buffer time	-0.0303
Rebuffer percentage	-0.2733
Rebuffer count	-0.2505
Average rendered bitrate	0.5118
Bitrate switch count	0.1334
Average bitrate switch magnitude	0.1583

are appropriate for each quality metric of interest: 1-second bin, 5% bin, unit bin, 360 kbps-sized bin, unit, and 600 kbps-sized bin for initial buffering time, rebuffer percentage, rebuffer count, average rendered bitrate, bitrate switch count, and average bitrate switch magnitude, respectively. The results of ANOVA suggest that initial buffer time is the only factor that is statistically insignificant to MOS.

Given the poor performance of isolated quality metric. A natural question is: Does combination of metrics provide more insights? To answer the question, we plot the cross metric correlation in Fig. 4.6. Most metric pairs perform quite independently, which indicates metrics supplement each other. Therefore, there is a great potential for a combination of metrics to provide a better performance than the isolated metrics. At this juncture, it may be prudent to apply regression analysis on the expected improvement in the QoE prediction performance by combining different quality metrics for the following reasons. First, content providers are interested in the relative importance of the quality metrics in a unified model as they may want to know the top k metrics that they should monitor and optimize to improve user QoE. On the other hand, quantitative analysis on the joint effect of different quality metrics may provide a baseline solution to validate the improvement of state-of-the-art QoE models. Thus, we apply linear regression to the quality metrics.

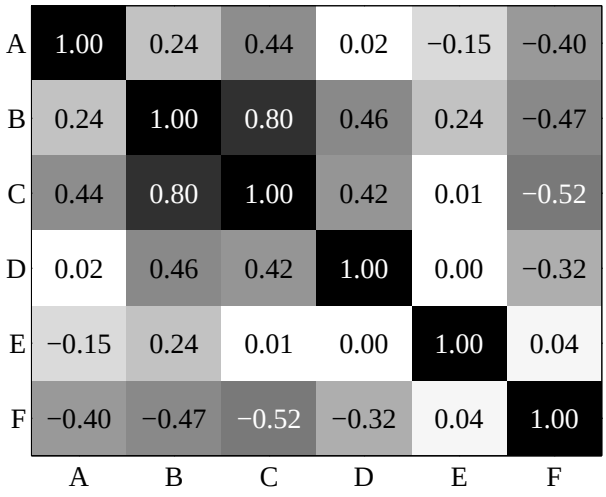


Figure 4.6: Metric correlation matrix. Initial buffer time, rebuffer percentage, rebuffer count, average rendered bitrate, bitrate switch count, and average bitrate switch magnitude are indexed from A to F.

Directly applying regression techniques with complex non-linear parameters could lead to models that lack a physically meaningful interpretation. While our ultimate goal is to extract the relative quantitative impact of the different metrics, doing so rigorously is outside the scope of this thesis. We randomly divide the video data into disjoint 80% training and 20% test subsets. To mitigate any bias due to the division of data, the process of randomly splitting the dataset is repeated 50 times. SRCC between the predicted and the ground truth quality scores are computed at the end of each iteration. The median correlation and its corresponding regression model are reported in Table 4.6. For clarity, rather than showing all combinations, we include 2, 3, and 4 variant regression models with the highest relative correlation. For all metrics, the combination with the average rendered bitrate provides the highest correlation while the combination of average rendered

Table 4.6: Median SRCC across 50 train-test combinations of regression models

Regression model	SRCC
-64.9P_r+0.0078$\overline{B}$+49.7	0.7215
-64.5P_r+0.0076$\overline{B}$+0.0006$\overline{B}_s$+50.3	0.7681
-1.7T_i-53.3P_r+0.0073$\overline{B}$+0.0006$\overline{B}_s$+53.3	0.7729

Table 4.7: Comparison of the existing QoE methods

QoE model	Stalling		Presentation quality		Switching
	Regression function	Influencing factors	Regression function	Influencing factors	Regression function
Liu's [41]	linear	stalling length	linear	bitrate	N/A
Yin's [85]	linear	stalling length	linear	bitrate	linear
FTW [28]	exponential	stalling length, # of stalling	N/A	N/A	N/A
Bentaleb's [5]	linear	# of stalling, stalling length	linear	SSIMplus	linear
Kim's [36]	N/A	N/A	exponential	packet loss packet jitter bandwidth efficiency	N/A
Mok's [47]	linear	stalling length, stalling frequency, initial buffering length	N/A	N/A	N/A
VsQM [61]	exponential	average stalling length per segment, # of stalling per segment, period per segment	N/A	N/A	N/A
Xue's [83]	logarithmic	stalling length, # of stalling, bit count of the stalling segment	linear	QP	N/A
Liu's [42]	polynomial	# of stalling, stalling length, magnitude of motion vector	exponential	VQM	quadratic
SQI [16]	combination of exponentials	# of stalling, stalling length, video quality of stalling segment	linear	SSIMplus	N/A

bitrate and rebuffer percentage achieves the highest correlation to MOS amongst bi-variant regression models. What is also worth mentioning is that although bitrate switch count and average bitrate switch magnitude are weakly correlated with MOS, the performance of linear regression model can be greatly improved by taking the video quality variation into consideration. The results further encourage exploration in the human perception of time-varying video quality.

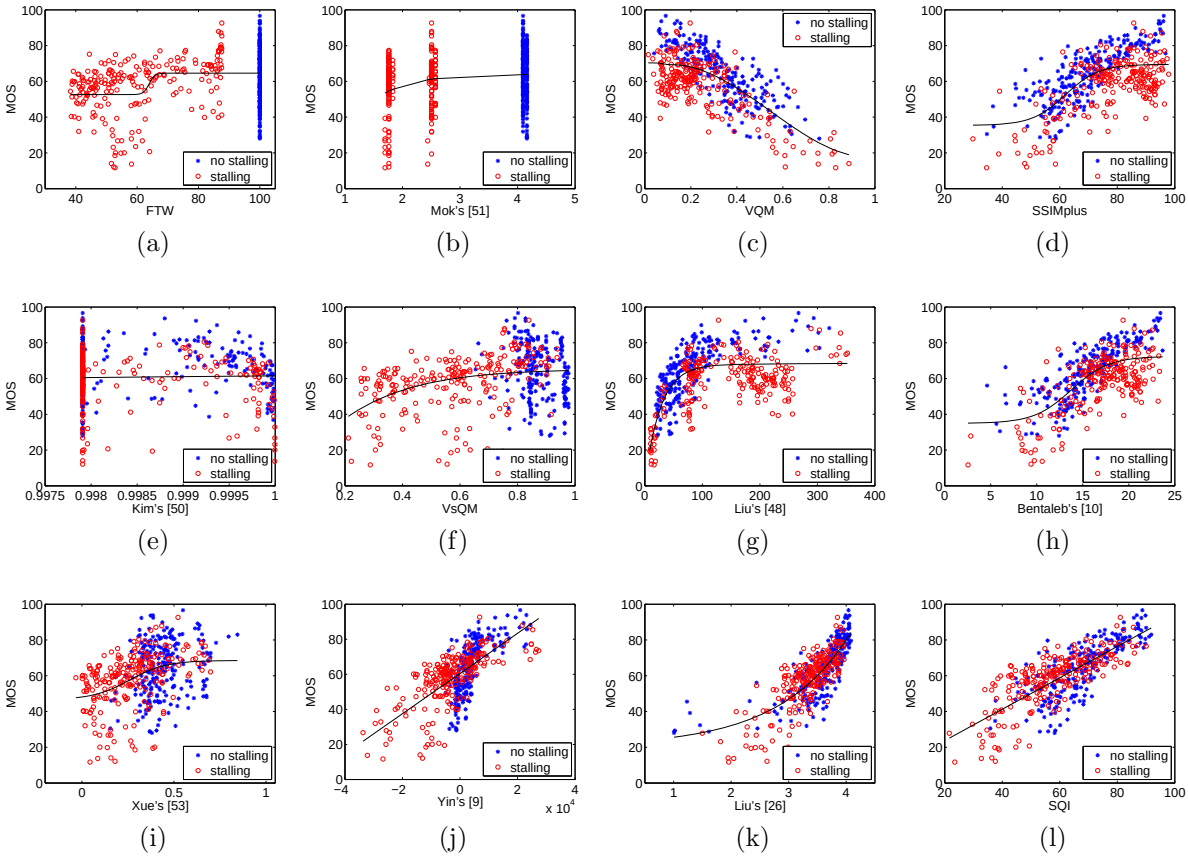


Figure 4.7: Predicted QoE vs. MOS.

4.2.5 Performance of Existing Objective QoE Models

Using the Waterloo SQoE-II database, we test the performance of ten state-of-the-art QoE models from three categories: network QoS-based, [36], application QoS-based [47, 61, 28, 41, 83, 85], and hybrid models of application QoS and signal fidelity [15, 42, 5]. A description of the ten QoE models is shown in Table 4.7. Since the source code of the QoE models is not publicly available, we try our best to implement the algorithms that preserve as much details of the original implementations as possible under the instruction

of the original authors. However, we do not claim perfect reproduction of the algorithms because the databases that the QoE models were developed upon are not publicly available for verification. For fairness, all models are tested using their default parameter settings. For Xue's [83], the model parameter c is not given in the original paper. We set $c = 0.05$ such that the model achieves its optimal performance on the current database. PLCC after nonlinear regression and SRCC are employed as the evaluation criteria for objective QoE models. Table 4.8 summarizes the evaluation results of the ten QoE models from three categories along with the two top VQA algorithms in terms of prediction accuracy and computational complexity. To compare the computational complexity of objective QoE algorithms, we measured the average computation time required to assess one streaming video (using a computer with Intel Core i7-4790 processor at 3.60 GHz). Scatter plots of objective scores vs. MOS for all the algorithms on the entire Waterloo SQoE-II database, along with the best fitting logistic functions, are shown in Fig. 4.7. These test results also provide some useful insights regarding the general approaches used in QoE models. First of all, it can be observed from the experiments that the stalling-centric QoE models [28][47][61] do not perform well on the database. The major reason is that stalling-centric models (i.e., FTW [28] and Mok's [47] do not take the presentation quality of the videos into consideration, which is often the most dominant QoE factor, and in many cases all other factors (such as stalling) become only secondary. Indeed, this is quite apparent from our test results, where even PSNR, a very crude presentation quality measure that does not take into account any initial buffering or stalling at all, performs significantly better than stalling-centric methods that ignore presentation quality. Second, the network QoS-based QoE model Kim's [36] also performs poorly because it ignores the characteristics of source

video and ABR algorithms. As we have shown in the Section 3.2.2 that both utilizing different ABR algorithms at the same network condition and using the same bitrate to encode different video content can lead to drastically different QoE. Third, it is clear from Fig. 4.7 that all QoE models except for SQI [16] fail to provide an adequate alignment to the clusters with and without stalling suggesting that it is important to capture the interactions between video presentation quality and the impact of stalling. Fourth, the cluster without stalling in the Fig. 4.7(c) and Fig. 4.7(d) is more compact than the one in the Fig. 4.7(k) and Fig. 4.7(h). Thus, penalizing quality degradation can improve the prediction accuracy of QoE models. On the other hand, SQI tends to overestimate the quality of sequences with large quality degradation, which also confirms that stability should be a concern of QoE. Fifth, despite their superior performances, Liu's [42] happen to overestimate the QoE of sequences with steep quality improvement. The results suggest that subjects do not appreciate abrupt quality improvement. However, the underlining mechanism of such phenomenon is still unknown and thus deeper investigations on the human perception on the time-varying video quality is desirable. Sixth, all models overestimate the QoE of live video sequence FCB at low bitrates suggesting that a content type-aware QoE model may further improve the performance of existing QoE models.

We carry out a F-test on the prediction residuals as described in Section 4.2.1. After comparing every possible pairs of objective models, the results are summarized in Table 4.9, where a symbol '1' means the row model performs significantly better than the column model, a symbol '0' means the opposite, and a symbol '-' indicates that the row and column models are statistically indistinguishable. The performance of QoE models can be roughly clustered into three levels based on the results of statistical significance test,

Table 4.8: Performance comparison of QoE models on Waterloo SQoE-II database. Signal fidelity-based, application QoS-based, network QoS-based, and hybrid models are indexed from A to D.

QoE model	Type	Prediction accuracy		Computation time in second	
		PLCC	SRCC	server	client
SSIMplus[58]	A	0.6519	0.5617	9.79	0
VQA[55]	A	0.6716	0.5650	244	0
Liu's [41]	B	0.6902	0.5145	0	5×10^{-5}
Yin's [85]	B	0.7028	0.7143	0	8.95×10^{-5}
FTW[28]	B	0.3506	0.2745	0	5.95×10^{-5}
Bentaleb's[5]	D	0.6888	0.6322	9.79	1.11×10^{-4}
Kim's [36]	C	0.0259	0.0196	0	5.55×10^{-5}
Mok's [47]	B	0.2448	0.1702	0	1.57×10^{-4}
VsQM[61]	B	0.3375	0.2010	0	1.23×10^{-4}
Xue's [83]	B	0.3973	0.3840	0	1.36×10^{-3}
Liu's [42]	D	**0.8170**	**0.8039**	244	4.67×10^{-4}
SQI[16]	D	0.7751	0.7707	9.79	7×10^{-5}

wherein Liu's [42] and SQI are statistically superior to all other QoE models. While the two top performers of application QoS-based models Liu's [41] and Yin's [85], the two top performers of signal fidelity-based models SSIMplus[58] and VQM[55], and the worst hybrid model Bentaleb's[5] are statistically inferior than the tier-1 models, they outperform the last group which mainly consists of QoS-based models. It is quite apparent that hybrid QoE model is a promising research direction.

There is inherent variability amongst subjects in the quality judgment of a streaming video. It is important not to penalize an algorithm if the differences between the algorithm scores and MOS can be explained by the inter-subject variability. Therefore, we follow the recommendation in [67] to compare the objective QoE models with the theoretical null model. Specifically, we compute the ratio between the variances of residuals between the

Table 4.9: Statistical significance matrix based on F-statistics on the Waterloo SQoE-II database. A symbol "1" means that the performance of the row model is statistically better than that of the column model, a symbol "0" means that the row model is statistically worse, and a symbol "-" means that the row and column models are Statistically indistinguishable

	SSIMplus [58]	VQM [55]	Liu's [41]	Yin's [85]	FTW [28]	Bentaleb's [5]	Kim's [36]	Xue's [83]	Mok's [47]	VsQM [61]	Liu's [42]	SQI [16]
SSIMplus[58]	-	-	-	-	1	-	1	1	1	1	0	0
VQM[55]	-	-	-	-	1	-	1	1	1	1	0	0
Liu's[41]	-	-	-	-	1	-	1	1	1	1	0	0
Yin's[85]	-	-	-	-	1	-	1	1	1	1	0	0
FTW's[28]	0	0	0	0	-	0	-	-	-	-	0	0
Bentaleb's[5]	-	-	-	-	1	-	1	1	1	1	0	0
Kim's[36]	0	0	0	0	-	0	-	-	-	-	0	0
Xue's[83]	0	0	0	0	-	0	-	-	-	-	0	0
Mok's[47]	0	0	0	0	-	0	-	-	-	-	0	0
VsQM[61]	0	0	0	0	-	0	-	-	-	-	0	0
Liu's[42]	1	1	1	1	1	1	1	1	1	1	-	-
SQI[16]	1	1	1	1	1	1	1	1	1	1	-	-

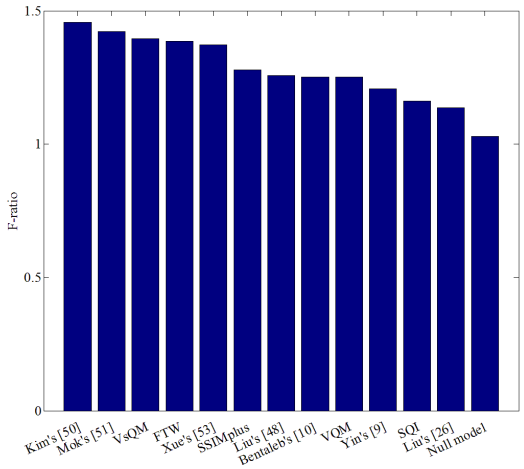


Figure 4.8: F-ratios for each objective models and theoretical null model.

individual ratings of all streaming videos and the corresponding MOS and the residual between individual ratings and the algorithm prediction of QoE (after non-linear regression). The ratio of two variances forms the F-statistic under central limit theorem. The null hypothesis is that the variance of the model residual is statistically indistinguishable (with 95% confidence) to the variance of the null residual. A threshold F-ratio can be determined based on the degrees of freedom in the numerator and denominator, along with the confidence level, where the numerator and denominator degrees of freedom in the F-test is obtained by subtracting one from the number of samples. Values of the F-ratio larger than the threshold indicates the objective QoE model and the null model are statistically distinguishable, and thus cause us to reject the null hypothesis. Otherwise, we accept the null hypothesis - *i.e.*, the performance of the objective QoE model is equivalent to the theoretical null model. The variance of the residuals from the null model and each of the 12 objective QoE models are shown in Fig. 4.8, wherein none of the QoE models is equivalent to the theoretical null model. It is quite apparent from our results that there remains considerable opportunity to improve the performance of objective QoE models despite significant progress.

To determine whether an objective QoE model can be used to compare the performance of ABR algorithms, we further compute SRCC on the MOS and the objective QoE prediction of the six ABR algorithms across different network conditions. Table 4.10 summarizes the evaluation results, which are somewhat disappointing because state-of-the-art QoE models do not seem to provide adequate comparisons on the ABR algorithms. Even the model with the best performance is only moderately correlated with subjective scores, which suggests a more accurate QoE model should be developed to objectively compare

Table 4.10: Prediction accuracy of the objective QoE models on the performance of adaptation algorithms

Network profile index	SSIMplus [58]	VQM [55]	Liu's [41]	Yin's [85]	FTW [28]	Bentaleb's [5]	Kim's [36]	Xue's [83]	Mok's [47]	VsQM [61]	Liu's [42]	SQI [16]
I	0.92	-0.92	0.92	0.20	0.20	0.20	-0.20	0.20	1.00	0.20	-1.00	0.20
II	-0.09	0.60	-0.09	0.09	0.71	0.26	0.37	-0.03	0.71	0.31	0.14	0.77
III	0.60	-0.60	0.49	-0.20	-0.58	0.66	0.09	-0.43	-0.54	-0.43	0.83	0.54
IV	1.00	-1.00	0.94	0.09	-0.37	0.94	-0.03	-0.83	-0.43	-0.83	0.37	0.09
V	0.49	-0.49	0.49	0.87	-0.46	0.54	0.77	0.09	-0.52	-0.35	0.89	0.83
VI	0.77	-0.65	0.71	0.77	-0.14	0.94	0.60	-0.71	-0.23	-0.77	0.60	0.83
VII	0.83	-0.83	0.60	0.94	0.14	0.71	0.37	-0.09	-0.12	0.09	0.60	0.66
VIII	0.77	-0.77	0.77	0.89	-0.33	0.94	0.03	-0.03	-0.43	-0.37	0.94	0.89
IX	-0.14	-0.14	-0.03	-0.37	0.26	0.26	-0.52	0.03	0.20	-0.43	-0.14	-0.14
X	0.89	-0.71	0.60	0.26	-0.70	1.00	0.26	-0.60	-0.71	-0.71	0.26	0.60
XI	0.77	-0.77	0.26	-0.09	-0.03	0.77	-0.60	-0.09	-0.66	-0.14	-0.14	-0.03
XII	0.89	-0.89	0.77	0.77	-0.03	0.77	0.03	0.09	-0.14	-0.03	0.94	0.77
XIII	0.71	-0.71	0.77	0.71	0.03	0.77	-0.97	-0.03	-0.31	0.09	0.94	0.94
Average	0.65	-0.61	0.55	0.38	-0.10	0.67	0.02	-0.19	-0.17	-0.26	0.40	0.53

the performance of ABR algorithms.

4.3 Discussion

The video sequences generated for the subjective study closely represent video experiences delivered under real-world conditions. This feat is achieved by employing the most commonly used adaptation strategies, modeling typical network conditions, and using a wide variety of video content types. As a result, the proposed database provides us the opportunity to compare performance of various approaches used for video QoE measurement in a video delivery chain. These approaches can be categorized into three types based on availability of content at various locations in the chain: server-side, network-side, and client-side. We have all the ingredients required to answer one of the most important questions related to understanding viewer experience: *where should we deploy the video QoE monitoring system?*

The QoE prediction performance of the three approaches is primarily dependent on the relevance of information available, at a location, corresponding to the viewer experience on an adaptive streaming client. The server-side measurement benefits from availability of video source. The impact of compression artifacts on video QoE can be better understood using reference based perceptual video quality measurement algorithms as shown in Table 4.4. However, video stalling and switching related impairments are not known at the server-side. Therefore, the server-side measurement is ideally suited for measuring preservation of creative intent, hereby referred to as *presentation QoE* of video content. Network-side algorithm do not typically have the luxury to process the content at a pixel level due to high data transmission rates and possible encryption of video content. As a result, these algorithms typically rely on transport-layer level information, that limits their capability to accurately predict video QoE. Client-side approaches can be based on content quality as well as impairments caused by network conditions: stalling and switching. However, computational resources and capability of light-weight no-reference approaches is often very limited. As a result client-side algorithm suffer from their inability to measure presentation quality. Therefore, the client-side measurement is ideally suited for measuring *network QoE* of video content.

None of the approaches are ideally suited for measurement of *overall video QoE* with high accuracy. In order to achieve the best of both worlds, presentation QoE can be delivered to the client-side as part of meta-data downloaded by a client. The availability of presentation QoE allows a client to understand the impact of the three dominant impairments, i.e., video compression, stalling, and switching, on video QoE. A client-side hybrid QoE measurement approach may not always be feasible. A cloud-based hybrid

QoE measurement systems provides an alternative to the client-side approach. A QoE server co-located with a streaming media server constantly monitors the streaming activities, such as stalling and switching, and stores the presentation quality measurements. The presentation quality measurements are combined with streaming activities to measure the hybrid QoE of a particular streaming session,. As a result, the hybrid approach has the potential to achieve the best video QoE prediction accuracy compared to the three standalone approaches while alleviating the power consumption of client device. Performance comparison between the four approaches towards video QoE measurement, provided in Table 4.8, points to the same qualitative conclusion. The table also compares the approaches in terms of their computational complexity. The best performing approach would provide the highest accuracy within available computational resources. The hybrid QoE methods Liu's[42] and SQI[16] achieve this feat among the methods under comparison.

4.4 Summary

Our work represents one of the first attempts to bridge the gap between the presentation VQA and stalling-centric models in QoE prediction. We assessed twelve QoE models with statistical analysis. Extensive experiments demonstrate the effectiveness of the proposed objective QoE model. Last, we shed light on the development QoE measurement algorithms and practical deployment of real-time QoE monitoring systems.

Chapter 5

Conclusion and Future Work

We have presented two subjective studies to understand human visual QoE of streaming video and proposed an objective model to characterize the perceptual QoE. Our work represents one of the first attempts to bridge the gap between the presentation VQA and stalling-centric models in QoE prediction. The subjective experiment reveals some interesting relationship between the impact of stalling and the instantaneous presentation quality. The Waterloo SQoE-II database is the first publicly available large scale HAS database dedicated to benchmark the performance of objective QoE models. The data set is diverse in terms of video content, and is both realistic and diverse in distortion types. We systematically assessed twelve QoE models with statistical analysis and shed light on the development of adaptation algorithms, QoE measurement algorithms, and practical deployment of real-time QoE monitoring systems. Extensive experiments also demonstrate that the proposed SQI model is simple in expression and effective in performance.

Future research may be carried out in many directions. First, other existing and future

QoE models may be tested and compared by making use of the database. Second, although pioneer researchers have made several attempts in the objective quality assessment of time-varying videos, the resultant objective models are not validated in a systematic manner, and are lack of explanation power. Thus, an objective QoE model that incorporate spatio-temporal aspects of videos and that predict human reactions to spatial adaptation and temporal adaptation could ultimately help video streaming approaches allocate resources in a more efficient way. Third, optimization of the existing video streaming frameworks based on QoE models is another challenging problem that is worth further investigations.

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