

A Brief Survey on Adaptive Video Streaming Quality Assessment

Wei Zhou^{a,b}, Xionguo Min^c, Hong Li^d, Qiuping Jiang^{d,*}

^a*Department of Electrical and Computer Engineering, University of Waterloo, Waterloo, ON N2L 3G1, Canada*

^b*CAS Key Laboratory of Technology in Geo-Spatial Information Processing and Application System, University of Science and Technology of China, Hefei 230027, China*

^c*Institute of Image Communication and Network Engineering, Shanghai Jiao Tong University, Shanghai 200240, China*

^d*School of Information Science and Engineering, Ningbo University, Ningbo 315211, China*

Abstract

Quality of experience (QoE) assessment for adaptive video streaming plays a significant role in advanced network management systems. It is especially challenging in case of dynamic adaptive streaming schemes over HTTP (DASH) which has increasingly complex characteristics including additional playback issues. In this paper, we provide a brief overview of adaptive video streaming quality assessment. Upon our review of related works, we analyze and compare different variations of objective QoE assessment models with or without using machine learning techniques for adaptive video streaming. Through the performance analysis, we observe that hybrid models perform better than both quality-of-service (QoS) driven QoE approaches and signal fidelity measurement. Moreover, the machine learning-based model slightly outperforms the model without using machine learning for the same setting. In addition, we find that existing video streaming QoE assessment models still have limited performance, which makes it difficult to be applied in practical communication systems. Therefore, based on the success of deep learned feature representations for traditional video quality prediction, we also apply the off-the-shelf deep convolutional neural network (DCNN) to evaluate the perceptual quality

*Corresponding author

Email address: jiangqiuping@nbu.edu.cn (Qiuping Jiang)

of streaming videos, where the spatio-temporal properties of streaming videos are taken into consideration. Experiments demonstrate its superiority, which sheds light on the future development of specifically designed deep learning frameworks for adaptive video streaming quality assessment. We believe this survey can serve as a guideline for QoE assessment of adaptive video streaming.

Keywords: Quality of experience, video quality assessment, adaptive streaming, performance analysis, deep convolutional neural network, spatio-temporal characteristics.

1. Introduction

With the rapid development of network services and mobile devices, streaming related multimedia applications have obtained tremendous growth. The arrival of dynamic adaptive streaming schemes over HTTP (DASH) standard [1] provides the transition from traditional connection-based video streaming protocols to hypertext transfer protocol (HTTP) adaptive streaming (HAS) protocols which enable flexible deployment, reduced workload, and reliable delivery. In addition, data analysis and artificial intelligence have emerged in a service-driven next-generation wireless communication network [2]. Therefore, quality of experience (QoE) for HAS streaming videos has attracted increasing attention in both academia and industry [3, 4].

As defined by the Telecommunication Standardization Sector of International Telecommunication Union (ITU-T), QoE is the overall acceptability of an application or service as perceived subjectively by the end user [5]. Addressing the QoE expectations of end-users is crucial for satisfying the requirements of video streaming services. Since users are the ultimate viewers of streaming videos in most practical applications, subjective QoE assessment [6, 7, 8] is straightforward and reliable for the evaluation of perceptual video streaming quality. Specifically, user studies are conducted, in which a number of subjects are asked to rate the visual quality of different streaming videos. The average of these subjective judgments, i.e. mean opinion score (MOS), is computed for

the final quality measurement, which is usually known as the ground truth.

Despite the fact that subjective QoE assessment can deliver the most precise and reliable evaluation, these subjective tests are time-consuming, expensive, and inconvenient. More importantly, they cannot be applied to the real-time multimedia distribution and playback scheduling frameworks. Hence, it is also increasingly desirable to develop highly effective and accurate objective QoE assessment models [9, 10, 11, 12] with low computational complexity for streaming videos, which aims to maintain efficient resource allocation and quality management for existing video services in multimedia delivery systems.

Building an effective QoE assessor for adaptive video streaming faces several foreseeable challenges. First, in addition to compression artifacts, how to evaluate the perceived quality of streaming video is more complicated due to additional network impairments (e.g. initial buffering, playback stalling, etc.), which is one of the main differences between traditional VQA and adaptive streaming quality assessment. Second, due to the time-consuming subjective experiments, the established databases for video streaming QoE are relatively small-scale, thus it is difficult to train a deep learning-based model with specific network parameters [13]. Third, the quality degradation of video streaming is influenced not only by video spatial characteristics, but also by its temporal attributes.

Figure 1 shows the important role of QoE assessment in multimedia communication systems. It illustrates that application servers transmit adaptive video streaming data to users through the core network, access network, and terminal devices. Then, the designed QoE assessor is deployed to take relevant information, e.g. the decoded streaming video data as input, and predicts perceptual video streaming quality. Finally, the virtually located QoE management receives the information from the QoE assessor and aims to optimize the network delivery of streaming video data.

Although various surveys have been proposed for the perceptual quality assessment of images/videos [14, 15, 16], such reviews for adaptive video streaming quality assessment are relatively scarce. Towards this end, we present an

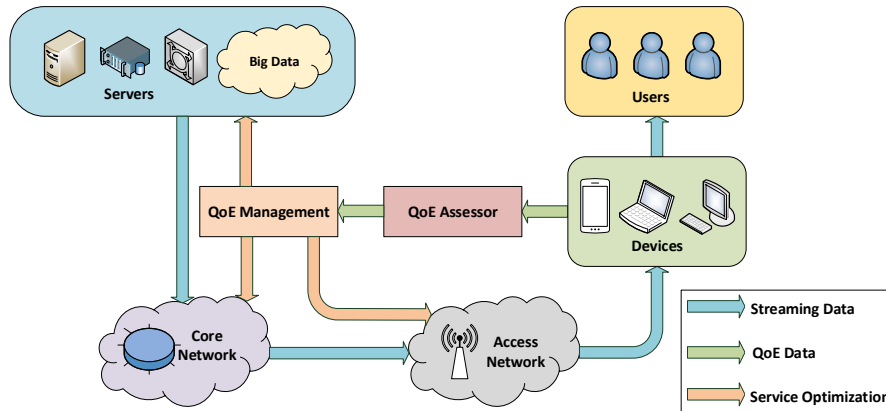


Figure 1: The important role of QoE assessment in multimedia communication systems. The designed QoE assessor is deployed to take the decoded streaming video data as input, and then predicts perceptual video streaming quality for the service optimization.

overview of QoE assessment for adaptive video streaming. The main contributions of this paper are summarized in three-fold as follows:

- We review subjective QoE assessment studies for adaptive video streaming, where the details of various subjective quality databases are described. Different from traditional video subjective QoE assessment, we discuss particular quality factors in these constructed databases.
- We review existing objective QoE assessment models for adaptive video streaming, including quality-of-service (QoS) driven user QoE assessment, signal fidelity measurement, and hybrid models.
- We analyze and compare objective QoE assessment models with or without using machine learning for adaptive video streaming. Besides, we exploit the deep feature representations from off-the-shelf DCNN models, which is consistent with spatio-temporal human visual perception. Experiments demonstrate its superior performance, leading to the promising future direction to develop streaming-aware quality prediction frameworks based on DCNN.

The structure of this article is as follows. In Section 2 and Section 3, we review the relevant subjective quality databases and existing objective QoE assessment models for adaptive video streaming, respectively. In Section 4, we analyze and compare different variations of QoE assessment models with or without using machine learning for adaptive video streaming. Additionally, the deep feature representations from off-the-shelf DCNN models show promising results against state-of-the-art methods, which sheds light on the future development of specific deep learning-based quality evaluation frameworks for adaptive video streaming. We conclude the results and discuss some future directions in Section 5.

2. Subjective Studies

The perceptual quality of HAS streaming videos not only suffers from compression distortions, but also degrades due to some streaming-specific issues, such as initial buffering, playback stalling, etc. Up to now, some subjective quality databases have been built for severing as the benchmarks for objective QoE assessment models. Here, we give an introduction to the mainstream publicly available subjective databases for adaptive video streaming during the past decade. The details of publicly available subjective databases for adaptive video streaming can be found in Table 1.

Table 1: Details of Publicly Available Subjective Databases for Adaptive Video Streaming.

Databases	# of Source Videos	# of Distorted Videos	# of Codecs	Viewing Displays
LIVEMVQA [17]	10	300	1	Phone & Tablet
LIVEQHVS [18]	3	15	1	HDTV
LIVEMSV [19]	24	180	0	Phone
WaterlooSQoE-I [20]	20	180	1	HDTV
LIVE-NFLX-I [21]	14	112	1	Phone
WaterlooSQoE-II [22]	12	588	1	HDTV
WaterlooSQoE-III [23]	20	450	1	HDTV
LIVE-NFLX-II [24]	15	420	1	HDTV
WaterlooSQoE-IV [25]	5	1,350	2	Phone & HDTV & UHDTV

The earliest adaptive video streaming subjective database dates back to

2012 when Moorthy et al. proposed the LIVE mobile video quality assessment (LIVEMVQA) database [17]. This database consists of 10 source videos and 300 test videos. The distortion types include H.264 compression, wireless channel packet loss, frame freezes, rate adaptation, and temporal dynamics. In the subjective test, 200 distorted videos evaluated by over 30 subjects on a small phone, as well as 100 distorted videos rated by 17 subjects on a larger tablet device.

The LIVEQHVS [18] contains 3 original reference videos. The length of each video is relatively long, which is 300 seconds duration. The long videos are constructed by concatenating 8 high-quality short video clips. For each source video, 6 quality-varying videos are generated by applying various encoding bitrates of H.264 encoder. Among these 18 distorted videos, 3 of them are used for the training of subjective studies, the remaining 15 quality-varying videos are exploited for testing. These video sequences are displayed to the subjects on a 58-inch high definition television (HDTV) monitor.

The LIVEMSV [19] includes 24 pristine videos with either 1280×720 pixels or 640×360 pixels. Since this database focuses on network impairments, other factors such as spatial distortions are minimized. There exist 180 distorted videos produced by all the reference videos with 26 unique hand-crafted stalling events. The subjective quality labels are obtained from 54 subjects, leading to 4,830 human opinions. The viewing display is Apple iPhone 5.

The WaterlooSQoE-I [20] considers both the compression and playback artifacts. With H.264 encoder, the original source videos are encoded into three bitrate levels which include 500 Kbps, 1,500 Kbps, and 3,000 Kbps. Note that these three bitrate levels are based on commonly available parameters of video transmission over wireless communication networks. In addition, playback issues are also taken into account in this database. To be specific, apart from the introduced compression distortions, a five-second stalling event is then simulated at either the beginning or the middle time point of the encoded video sequences. Therefore, the initial buffering and middle playback stalling streaming videos can be produced by this kind of simulation. In total, this database is

made up of 200 videos containing 20 source videos, 60 encoded videos, 60 initial buffering videos, and 60 middle playback stalling videos. A subjective study is conducted to collect ratings of test videos on the HDTV display.

The LIVE-NFLX-I [21] is presented to investigate the influence of mixtures from adaptive streaming video artifacts. The database is composed of 14 source video contents and 112 distorted videos obtained by encoding the original videos using H.264 encoder. There are 8 different playout patterns including dynamically changing H.264 compression rates, rebuffering events, and the mixtures of both. The subjective experiment is conducted by 55 subjects on a mobile device. It should be noted that only three reference videos and their corresponding distorted videos are made publicly available in this database.

The WaterlooSQoE-II [22] involves 12 source videos, where each video has 8 seconds duration and is further partitioned into 4-second short segments. The short segments are encoded into seven representations with H.264 codec. To simulate quality adaptation events, two consecutive 4-second segments with different representations are concatenated from the same video content, resulting in 588 videos with variations in compression level, spatial resolution, and frame rate. The videos are displayed at their pixel resolution on the HDTV display for subjective quality collections.

The above-mentioned subjective quality databases for adaptive video streaming have a common issue that they are hand-crafted. That is, these databases are far away from real-world streaming video distributions. Therefore, the following recently established databases aim to tackle this problem, including WaterlooSQoE-III [23], LIVE-NFLX-II [24], and WaterlooSQoE-IV [25].

Specifically, the WaterlooSQoE-III [23] and the LIVE-NFLX-II [24] have 450 and 420 realistic adaptive streaming videos, respectively. Both databases integrate actual network traces to capture realistic network variations. Different realistic adaptive bitrate (ABR) streaming algorithms [26, 27, 28] are employed for video delivery. The subjective experiments conducted on the HDTV are used to obtain subjective QoE ratings. The WaterlooSQoE-IV [25] provides so far the most comprehensive QoE assessment database which consists of 1,350

subjective-rated streaming videos that are derived from a variety of source video contents, video codecs, network conditions, ABR algorithms, and viewing displays. For example, except for mobile phone and HDTV, the Ultra HDTV (UHDTV) is also applied in subjective studies.

With these subjective quality databases for adaptive video streaming, effective quality labels are provided for designing objective quality assessment algorithms, which facilitates researchers to propose objective quality assessment models that are closer to human visual perception. Besides, we can measure and compare the performance of different adaptive video streaming quality evaluation models on these databases.

3. Objective Models

In general, according to the existence of original reference videos, traditional objective Video QoE Assessment (VQA) methods can be classified into full-reference (FR) VQA, reduced-reference (RR) VQA, and no-reference (NR) VQA. Specifically, FR VQA methods [29, 30, 31] require the corresponding original reference video. The RR VQA methods assume that a portion of the reference video is available, which can be some parameters extracted from the original content or additional side information added to the test video. The NR VQA algorithms [32, 33, 34] evaluate visual quality without any information from the corresponding original reference video, which are more practical in application scenarios.

In the literature, there have emerged several objective quality assessment models for adaptive video streaming. Apart from the classification method of conventional VQA methods that is based on the information of original reference videos, existing video streaming QoE assessment models can be generally classified into three categories which include QoS driven user QoE assessment [35, 36], signal fidelity measurement [29, 30, 31], and hybrid models [20, 37]. Specifically, the QoS driven user QoE assessment exploits the causal relationship between QoS and QoE problems, while the signal fidelity measurement

takes the QoE assessment problem from the aspect of signal fidelity. The hybrid models comprehensively consider the QoS driven user QoE assessment and the signal fidelity measurement at the same time. Moreover, solid related work has been done on automatic video streaming QoE assessment models with or without using machine learning techniques. Table 2 lists the summary of objective QoE assessment models for adaptive video streaming. It should be noted that we only focus on the mentioned QoE assessment models for adaptive video streaming in this paper, other algorithms could be found in [38]. Compared to [38], we review some more recent video streaming subjective databases and QoE assessment models. Besides, we exploit the off-the-shelf DCNN to evaluate the video streaming quality from both spatial and temporal aspects, which provides promising cues about the design of specific frameworks for adaptive video streaming.

Table 2: Summary of objective QoE Assessment Models for Adaptive Video Streaming.

Methods	Learning	Types
FTW [35]	No	QoS driven user QoE assessment
VsQM [36]	No	QoS driven user QoE assessment
PSNR	No	Signal fidelity measurement
SSIM [29]	No	Signal fidelity measurement
MS-SSIM [30]	No	Signal fidelity measurement
SSIMplus [31]	No	Signal fidelity measurement
SQI [20]	No	Hybrid model
Video ATLAS [37]	Yes	Hybrid model

As for QoS driven user QoE assessment, the mapping functions between QoS and QoE problems are usually employed. For example, several QoS models such as FTW [35] and VsQM [36] have been proposed by utilizing global rebuffering statistics and the pattern of temporal local content importance. However, the video quality impairment caused by video compression has not been taken into consideration.

For signal fidelity measurement, conventional objective VQA metrics consider human visual perception rather than the simplest peak signal-to-noise ratio (PSNR), such as the structural similarity index (SSIM) [29], the multi-scale structure similarity index (MS-SSIM) [30], the SSIMplus [31], and so on. However, all of these algorithms are under the assumption that the playback can be exactly controlled. But in the applications of QoE assessment for HAS streaming videos, due to network transmission impairments, these services may suffer from some playback issues which could bring significant quality degradation.

Additionally, hybrid models integrate the scheme of QoS driven user QoE assessment with the scheme of signal fidelity measurement. In [20], a unified video streaming QoE assessor without using machine learning named streaming quality index (SQI) has been proposed, which combines FR quality metrics such as SSIM and MS-SSIM with stalling related information. In other words, the impact of compression and stalling are modeled simultaneously. Moreover, in [37], the machine learning-based model called video assessment of temporal artifacts and stalls (Video ATLAS) has been presented, where a number of QoE-related features, including objective quality features, rebuffering-aware features and memory-driven features, are utilized to predict the perceptual video streaming quality.

4. Performance Analysis

4.1. Performance Evaluation Criteria

According to the recommendation from the Video Quality Experts Group [39], we adopt two widely used criteria including the Spearman rank-order correlation coefficient (SROCC) and Pearson linear correlation coefficient (PLCC) to analyze and compare different objective algorithms for video streaming QoE assessment. The SROCC performance is utilized to measure QoE prediction monotonicity, while the PLCC performance is applied to evaluate QoE prediction accuracy.

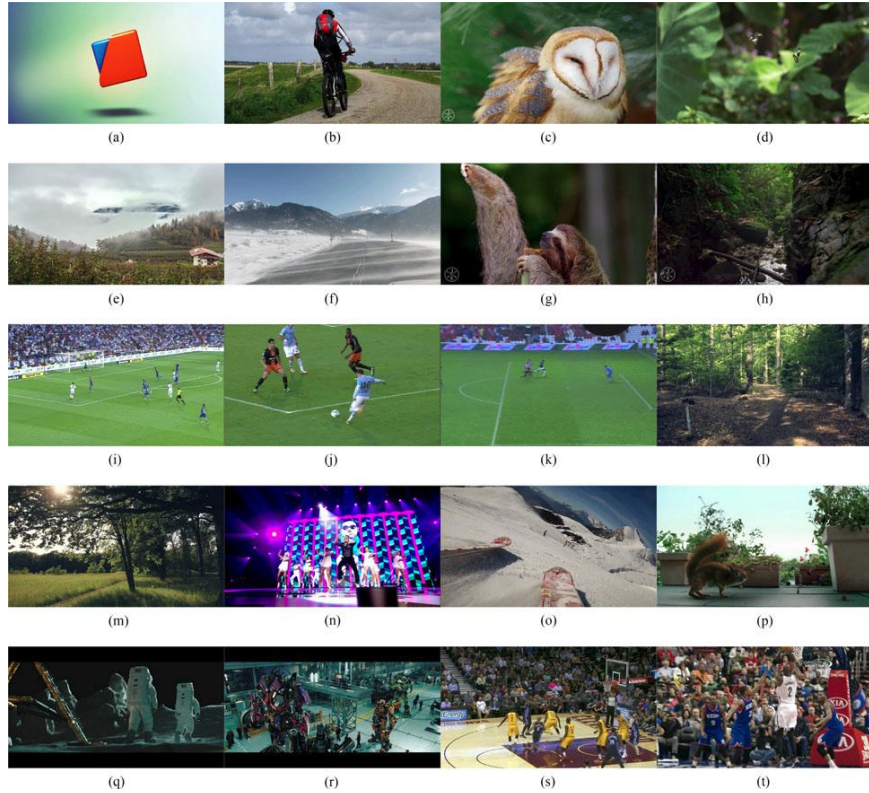


Figure 2: Video contents in WaterlooSQoE-I database [20].

Moreover, before computing the PLCC performance of objective QoE assessment algorithms, a nonlinear logistic fitting is generally used to map the predicted quality scores to the same scales of subjective quality ratings. Here, higher SROCC and PLCC correlation coefficients indicate better performance and agreement with subjective human quality perception.

4.2. Results of Video Streaming QoE Models

Considering that existing adaptive video streaming QoE assessment models consist of QoS driven QoE methods, signal fidelity measurement, and hybrid approaches which combine FR quality metrics with rebuffering related features, we conduct experiments on the representative WaterlooSQoE-I database [37]. The

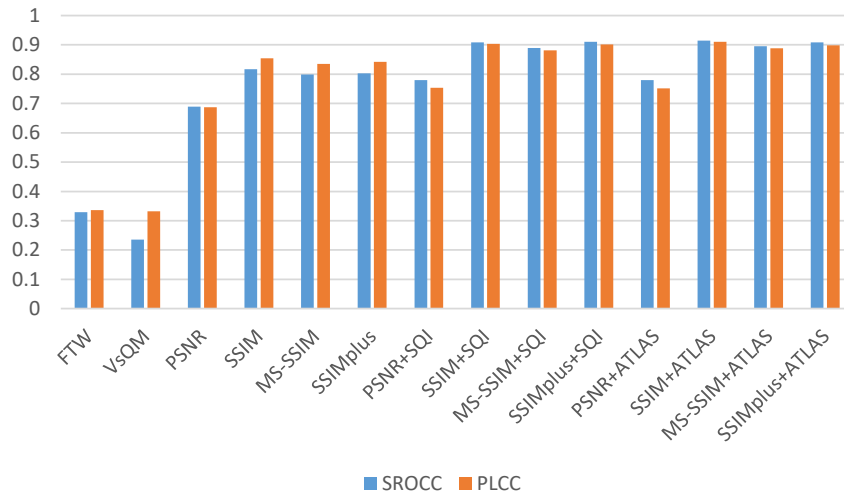


Figure 3: Performance comparison of existing video streaming QoE assessment models on WaterlooSQoE-I database [20].

reason for choosing the WaterlooSQoE-I database is that it is the first database containing the most abundant video contents and codecs. Figure 2 shows that there exist 20 original reference videos consisting of diverse video contents in the WaterlooSQoE-I database [20]. With these pristine sources, streaming videos impaired from both compression distortions and playback issues can be generated.

We first analyze different variations of objective quality assessment models with or without using machine learning for adaptive video streaming. Figure 3 shows the performance comparison of existing video streaming QoE assessment models on WaterlooSQoE-I database [20]. In this figure, the Video ATLAS is the only machine learning-based method. And the regression model with the best SROCC performance is reported.

In general, as we can see from Figure 3, hybrid models outperform QoS driven QoE models (i.e. FTW and VsQM) as well as the signal fidelity measurement when using the same FR quality metrics. This is mainly because hybrid models are the combination of QoS driven user QoE assessment and sig-

nal fidelity measurement, which could lead to better performance. Additionally, the machine learning-based QoE assessment model, namely Video ATLAS, is slightly superior to the SQI model without using machine learning for the same FR quality metrics combination. One possible explanation is that the machine learning-based method learns distortion-related features better directly from streaming videos.

Based on these observations, we can conclude that existing video streaming QoE assessment algorithms still have limited performance, making it difficult to be employed in practical applications. At the same time, deep learning models have been studied to understand the development of human sensory cortical processing [40]. Besides, deep convolutional neural network (DCNN) has been applied to perceptual quality assessment, which demonstrates the remarkable ability of DCNN to learn discriminative features for addressing this challenging task [41, 42, 43, 44]. However, to the best of our knowledge, there is no similar research work about deep learning solutions to hybrid NR video streaming QoE assessment based on spatio-temporal visual content features in streaming videos. Thus, we apply a simplified framework to tackle the adaptive video streaming quality assessment, where we only exploit distorted streaming videos without referring to the corresponding source videos. That is, this method belongs to the category of no-reference video streaming QoE models, which is more practical in real applications.

Specifically, considering that a streaming video sequence is composed of many video frames, we first extract multiple distorted video frames from streaming video sequences. Apart from the spatial characteristics of different distorted video frames, note that a video sequence is a set of consecutive video frames which contain a variety of motion attributes. In other words, the temporal variation of video contents could affect the visual perception of the HVS to a certain degree. Thus, compared to image quality prediction, video streaming QoE assessment is more complex due to the additional temporal quality variation. We then utilize frame difference maps to take the temporal factor into account, which are simply defined as the difference between adjacent video frames.

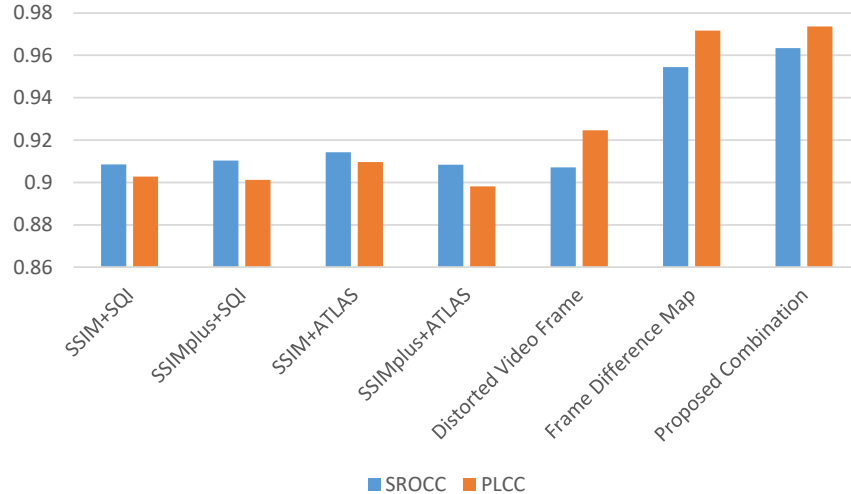


Figure 4: Performance comparison of the extended video streaming QoE assessment model and state-of-the-arts on WaterlooSQoE-I database [20].

The two pre-trained DCNN models take distorted video frames and frame difference maps as inputs to extract the 2,048-dim features from the pool5 layer. Note that the two employed ResNet50 architectures have the same configuration and share weights with each other. Then, the concatenation of the extracted 2,048-dim features constitute a 4,096-dim feature vector. Finally, the well-known regression model (i.e. SVR) is applied to map the 4,096-dim feature vector into the ultimate perceptual quality score for each streaming video. In addition, it should be noted that the used database is randomly divided into 80% for training and the remaining 20% for testing. We perform 1,000 iterations of cross correlation, and then give the median SROCC and PLCC values as the final measurement.

Figure 4 shows the performance comparison with state-of-the-art video streaming QoE models. Note that we choose the top two algorithms shown in Figure 3 to be compared, which include no machine learning (i.e. SSIM+SQI and SSIMplus+SQI) and machine learning-based (i.e. SSIM+ATLAS and SSIMplus+ATLAS) video streaming QoE assessment models. We denote the deep

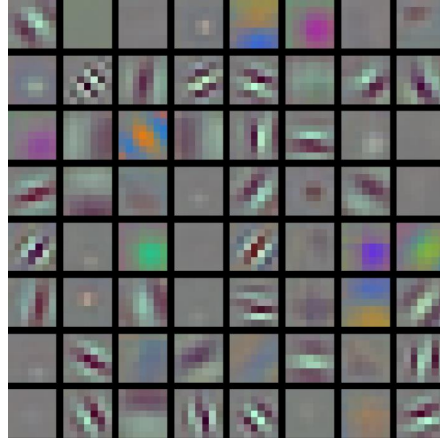


Figure 5: Visualization of learned kernels in the first convolutional layer for the pre-trained ResNet50 network. The learned kernels capture various intrinsic image texture patterns.

learning models as “Distorted Video Frame”, “Frame Difference Map”, and “Proposed Combination”, in which we separately apply the deep learned features from distorted video frames, frame difference maps, and the combination of distorted video frames and frame difference maps. As shown in this figure, the deep learning models perform better than the other methods. Moreover, only using frame difference maps outperforms that of only using distorted video frames. One possible explanation may be that the temporal motion attributes have more impact on the perceptual quality of streaming videos compared with that of the spatial texture characteristics. Additionally, the combination of spatial and temporal features outperforms either the spatial feature or the temporal feature alone, which further verifies the significance of spatio-temporal human visual perception in adaptive video streaming.

To reveal the discriminative information from deep learned features, Figure 5 presents the visualization of learned kernels in the first convolutional layer for the pre-trained ResNet50 network. It should be noted that the ResNet50 model is pre-trained on a large-scale dataset with diverse image contents, namely ImageNet [45]. Therefore, we can see that the learned kernels can capture intrinsic image texture patterns. In other words, the pre-trained ResNet50 model has

a promising ability to represent discriminative features for quality assessment, which sheds light on the future development of specifically designed deep learning models for adaptive video streaming quality evaluation. For example, the end-to-end learning DCNN combined with recurrent neural network could be explored.

5. Conclusion and Future Directions

In this paper, we present a brief survey of QoE assessment for adaptive video streaming. First, the QoE assessor plays a vital role in multimedia communication systems. Considering complex characteristics of streaming videos, many challenges are involved in the perceptual quality prediction task. We then review both subjective studies and objective models for adaptive video streaming quality assessment. Finally, we conduct comparisons of existing state-of-the-art QoE assessment models for streaming videos, with or without using machine learning techniques. The performance analysis shows that hybrid models outperform QoS driven QoE models and the signal fidelity measurement when using the same FR quality metrics. Furthermore, the machine learning-based QoE assessment model is demonstrated slightly superior to the model without using machine learning. However, these approaches still have limited performance for video streaming QoE assessment.

Additionally, we apply the deep feature representations from off-the-shelf DCNN models based on spatio-temporal human visual perception, which can deliver promising results. This demonstrates that specific deep learning frameworks for QoE assessment of adaptive video streaming should be addressed in the future. Furthermore, more comprehensive investigation about adaptive video streaming quality assessment could be considered, where the design of immersive 3D/stereoscopic video streaming QoE assessment methods based on deep neural networks is another research direction. For 3D video streaming QoE assessment, except for video quality, more quality dimensions should be taken into consideration, e.g. depth perception and visual comfort.

References

- [1] T. Stockhammer, Dynamic adaptive streaming over HTTP: standards and design principles, in: Proceedings of the Second Annual ACM conference on Multimedia Systems, 2011, pp. 133–144.
- [2] M. G. Kibria, K. Nguyen, G. P. Villardi, O. Zhao, K. Ishizu, F. Kojima, Big data analytics, machine learning, and artificial intelligence in next-generation wireless networks, *IEEE Access*, 2018 6 32328–32338.
- [3] M. Alreshoodi, J. Woods, Survey on QoE\QoS correlation models for multimedia services, arXiv preprint arXiv:1306.0221, 2013.
- [4] Z. Wang, A. Rehman, Begin with the end in mind: A unified end-to-end quality-of-experience monitoring, optimization and management framework, in: SMPTE Annual Technical Conference and Exhibition, 2017, pp. 1–11.
- [5] I.-T. T. S. Sector, O. ITU, Quality of experience requirements for IPTV services, Recommendation ITU-T G, 2008 1080.
- [6] K. Seshadrinathan, R. Soundararajan, A. C. Bovik, L. K. Cormack, A subjective study to evaluate video quality assessment algorithms, in: SPIE Human Vision and Electronic Imaging XV, 2010, Vol. 7527, pp. 128–137.
- [7] J. Y. Lin, R. Song, C.-H. Wu, T. Liu, H. Wang, C.-C. J. Kuo, MCL-V: A streaming video quality assessment database, *Elsevier Journal of Visual Communication and Image Representation*, 2015 30 1–9.
- [8] J. Xu, C. Lin, W. Zhou, Z. Chen, Subjective quality assessment of stereoscopic omnidirectional image, in: Springer Pacific Rim Conference on Multimedia, 2018, pp. 589–599.
- [9] S. Chikkerur, V. Sundaram, M. Reisslein, L. J. Karam, Objective video quality assessment methods: A classification, review, and performance comparison, *IEEE Transactions on Broadcasting*, 2011 57 (2) 165–182.

- [10] Q. Jiang, F. Shao, G. Jiang, M. Yu, Z. Peng, Supervised dictionary learning for blind image quality assessment using quality-constraint sparse coding, Elsevier Journal of Visual Communication and Image Representation, 2015 33 123–133.
- [11] L. Li, W. Xia, Y. Fang, K. Gu, J. Wu, W. Lin, J. Qian, Color image quality assessment based on sparse representation and reconstruction residual, Elsevier Journal of Visual Communication and Image Representation, 2016 38 550–560.
- [12] W. Zhou, Z. Chen, W. Li, Dual-stream interactive networks for no-reference stereoscopic image quality assessment, IEEE Transactions on Image Processing, 2019 28 (8) 3946–3958.
- [13] J. Kim, H. Zeng, D. Ghadiyaram, S. Lee, L. Zhang, A. C. Bovik, Deep convolutional neural models for picture-quality prediction: Challenges and solutions to data-driven image quality assessment, IEEE Signal Processing Magazine, 2017 34 (6) 130–141.
- [14] W. Lin, C.-C. J. Kuo, Perceptual visual quality metrics: A survey, Elsevier Journal of Visual Communication and Image Representation, 2011 22 (4) 297–312.
- [15] M. T. Vega, V. Sguazzo, D. C. Mocanu, A. Liotta, An experimental survey of no-reference video quality assessment methods, International Journal of Pervasive Computing and Communications, 2016.
- [16] G. Zhai, X. Min, Perceptual image quality assessment: A survey, Springer Science China Information Sciences, 2020 63 (11) 1–52.
- [17] A. K. Moorthy, L. K. Choi, A. C. Bovik, G. De Veciana, Video quality assessment on mobile devices: Subjective, behavioral and objective studies, IEEE Journal of Selected Topics in Signal Processing, 2012 6 (6) 652–671.
- [18] C. Chen, L. K. Choi, G. De Veciana, C. Caramanis, R. W. Heath, A. C. Bovik, Modeling the time varying subjective quality of HTTP video streams

- with rate adaptations, *IEEE Transactions on Image Processing*, 2014 23 (5) 2206–2221.
- [19] D. Ghadiyaram, A. C. Bovik, H. Yeganeh, R. Kordasiewicz, M. Gallant, Study of the effects of stalling events on the quality of experience of mobile streaming videos, in: *IEEE Global Conference on Signal and Information Processing*, 2014, pp. 989–993.
- [20] Z. Duanmu, K. Zeng, K. Ma, A. Rehman, Z. Wang, A quality-of-experience index for streaming video, *IEEE Journal of Selected Topics in Signal Processing*, 2017 11 (1) 154–166.
- [21] C. G. Bampis, Z. Li, A. K. Moorthy, I. Katsavounidis, A. Aaron, A. C. Bovik, Study of temporal effects on subjective video quality of experience, *IEEE Transactions on Image Processing*, 2017 26 (11) 5217–5231.
- [22] Z. Duanmu, K. Ma, Z. Wang, Quality-of-experience of adaptive video streaming: Exploring the space of adaptations, in: *Proceedings of the 25th ACM international conference on Multimedia*, 2017, pp. 1752–1760.
- [23] Z. Duanmu, A. Rehman, Z. Wang, A quality-of-experience database for adaptive video streaming, *IEEE Transactions on Broadcasting*, 2018 64 (2) 474–487.
- [24] C. G. Bampis, Z. Li, I. Katsavounidis, T.-Y. Huang, C. Ekanadham, A. C. Bovik, Towards perceptually optimized adaptive video streaming—a realistic quality of experience database, *IEEE Transactions on Image Processing*, 2021 30 5182–5197.
- [25] Z. Duanmu, W. Liu, Z. Li, D. Chen, Z. Wang, Y. Wang, W. Gao, Assessing the quality-of-experience of adaptive bitrate video streaming, *arXiv preprint arXiv:2008.08804*, 2020.
- [26] Z. Li, X. Zhu, J. Gahm, R. Pan, H. Hu, A. C. Begen, D. Oran, Probe and adapt: Rate adaptation for HTTP video streaming at scale, *IEEE Journal on Selected Areas in Communications*, 2014 32 (4) 719–733.

- [27] X. Yin, A. Jindal, V. Sekar, B. Sinopoli, A control-theoretic approach for dynamic adaptive video streaming over HTTP, in: Proceedings of the ACM Conference on Special Interest Group on Data Communication, 2015, pp. 325–338.
- [28] Z. Akhtar, Y. S. Nam, R. Govindan, S. Rao, J. Chen, E. Katz-Bassett, B. Ribeiro, J. Zhan, H. Zhang, Oboe: Auto-tuning video ABR algorithms to network conditions, in: Proceedings of the Conference of the ACM Special Interest Group on Data Communication, 2018, pp. 44–58.
- [29] Z. Wang, A. C. Bovik, H. R. Sheikh, E. P. Simoncelli, Image quality assessment: from error visibility to structural similarity, *IEEE Transactions on Image Processing*, 2004 13 (4) 600–612.
- [30] Z. Wang, E. P. Simoncelli, A. C. Bovik, Multiscale structural similarity for image quality assessment, in: The Thirty-Seventh IEEE Asilomar Conference on Signals, Systems & Computers, 2003, Vol. 2, pp. 1398–1402.
- [31] A. Rehman, K. Zeng, Z. Wang, Display device-adapted video quality-of-experience assessment, in: *Human Vision and Electronic Imaging XX*, 2015, Vol. 9394, International Society for Optics and Photonics, p. 939406.
- [32] Z. Chen, N. Liao, X. Gu, F. Wu, G. Shi, Hybrid distortion ranking tuned bitstream-layer video quality assessment, *IEEE Transactions on Circuits and Systems for Video Technology*, 2016 26 (6) 1029–1043.
- [33] W. Zhou, N. Liao, Z. Chen, W. Li, 3D-HEVC visual quality assessment: Database and bitstream model, in: *The Eighth IEEE International Conference on Quality of Multimedia Experience*, 2016, pp. 1–6.
- [34] Z. Chen, W. Zhou, W. Li, Blind stereoscopic video quality assessment: From depth perception to overall experience, *IEEE Transactions on Image Processing*, 2018 27 (2) 721–734.

- [35] T. Hoßfeld, M. Seufert, M. Hirth, T. Zinner, P. Tran-Gia, R. Schatz, Quantification of YouTube QoE via crowdsourcing, in: *IEEE International Symposium on Multimedia*, 2011, pp. 494–499.
- [36] D. Z. Rodriguez, J. Abrahao, D. C. Begazo, R. L. Rosa, G. Bressan, Quality metric to assess video streaming service over TCP considering temporal location of pauses, *IEEE Transactions on Consumer Electronics*, 2012 58 (3) 985–992.
- [37] C. G. Bampis, A. C. Bovik, Learning to predict streaming video QoE: Distortions, rebuffering and memory, *arXiv preprint arXiv:1703.00633*, 2017.
- [38] N. Barman, M. G. Martini, QoE modeling for HTTP adaptive video streaming—a survey and open challenges, *IEEE Access*, 2019 7 30831–30859.
- [39] V. Q. E. Group, et al., Final report from the video quality experts group on the validation of objective models of video quality assessment, in: *VQEG meeting*, Ottawa, Canada, March, 2000.
- [40] D. L. Yamins, J. J. DiCarlo, Using goal-driven deep learning models to understand sensory cortex, *Nature Neuroscience*, 2016 19 (3) 356.
- [41] M. Lopez-Martin, B. Carro, J. Lloret, S. Egea, A. Sanchez-Esguevillas, Deep learning model for multimedia quality of experience prediction based on network flow packets, *IEEE Communications Magazine*, 2018 56 (9) 110–117.
- [42] Y. Fang, J. Yan, X. Liu, J. Wang, Stereoscopic image quality assessment by deep convolutional neural network, *Elsevier Journal of Visual Communication and Image Representation*, 2019 58 400–406.
- [43] W. Zhou, Z. Chen, W. Li, Stereoscopic video quality prediction based on end-to-end dual stream deep neural networks, in: *Springer Pacific Rim Conference on Multimedia*, 2018, pp. 482–492.

- [44] W. Zhou, Z. Chen, Deep local and global spatiotemporal feature aggregation for blind video quality assessment, in: IEEE International Conference on Visual Communications and Image Processing, 2020, pp. 338–341.
- [45] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, L. Fei-Fei, ImageNet: A large-scale hierarchical image database, in: IEEE Conference on Computer Vision and Pattern Recognition, 2009, pp. 248–255.