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Video compression and optimization technologies - review

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***Abstract*—The use of video streaming is constantly increasing. High-resolution video requires resources on both the sender and the receiver side. Many compression techniques can be utilized to compress the video and simultaneously maintain quality. The main goal of this paper is to provide an overview of video streaming and QoE. This paper describes the basic concepts and discusses existing methodologies to measure QoE. Subjective, objective, and video compression technologies are discussed. This review paper gathers the codec implementation developed by MPEG, Google, and Apple. This paper outlines the challenges and future research directions that should be considered in the measurement and assessment of the quality of experience for video services.**

***Keywords*—video coding; compression; codec; MPEG**

I. INTRODUCTION

THE Online video services have grown exponentially since their inception. It has been predicted that, by 2022, 82% of all global internet traffic per year will be video content. According to the forecasts, this figure will continue to increase in the following years [1], and also mentioned in Statista Research [2]. Network speed and processing power is increasing, but on the other hand, video parameters – bit rate, frame rate, and resolution require more resources in the video compression system. Some methods can be used to compress videos and compactly optimize them. When videos are compressed, they can be stored or transmitted to viewers in an efficient manner [3]. The two organizations MPEG and ITU developed video coding standards [4]. That pioneer standard was H.261 and there have been extensions such as AVC/H,264, HEVC/H.265, and VVC/H.266. The objective of these standards was to double the compression ratio and retain the video quality of the video. Using these standards, it also increases the computation complexity and resource consumption [5].

The video sequence is encoded at different bit rates. These data rates are the constant bit rate (CBR) and variable bit rate (VBR) [6]. The use of one of these rate control modes depends on the streaming of the video. The application of these data rates has an impact on file size, encoding time, and video quality. Compression efficiency is highly dependent on bit rate for a given resolution and frame rate [7].

The aim of video compression is to minimise the bit rate and storage complexity and simultaneously retain video quality. There is continuous growth and high demand for video streaming services such as video on demand (VOD) and live streaming services. These services are provided by companies such as YouTube, Netflix, and Amazon Video. These service providers must meet the expectations of end users. It is essential to know the requirements of real users and measure the satisfaction and overall quality of experience (QoE) [8].

It is essential to determine the QoE of the end users. There is a demand for QoE models to measure QoE. These models can be based on subjective, objective, or hybrid evaluation [9]. These models utilize network and application level factors and predict the QoE of end users. The video resolution is FHD, UHD,4K, and 8K. The challenge of streaming these types of content requires high bandwidth and network resources to transmit this high-resolution content. There are a variety of codecs developed by MPEG and other vendors. These codecs should be investigated and applied to specific scenarios for video streaming. Every codec has its own limitations and possible applications in a particular context [10].

This paper focuses on a general overview of video streaming QoE. This paper provides state-of-the-art video coding and compression technologies. This also covers the methodologies utilized to measure video QoE. This paper analyzes the compression techniques and its suitability for video streaming applications, especially for FHD and 4K applications. In this study, we answer the following research questions:

1) What are the methodologies used to measure QoE of video streaming?
2) What compression techniques are utilized for video optimization?

The rest of the article is organised as follows. Section 2 describes the basic concepts of QoE of video streaming. It also lists the factors that have a potential impact on video QoE. This section describes the assessment methodologies used to measure video QoE. Section 3 provides an overview of video compression and its association with QoE. This section provides details about compression technologies. Section 4 demonstrates the existing video compression technologies in practice related to video streaming. This Section also includes the video codecs developed by various vendors. Section 5, summarizes the review, identifies challenges, and proposes future research work in this domain.

II. BACKGROUND

In this section, we will discuss the background information on QoE and the factors influencing QoE of video services. QoE and its important factors are shown in (Figure 1). We will also discuss the methods used to evaluate QoE.

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A. QoE Influence Factors

There are factors that could have an impact on QoE. These factors are classified as Human IFs, System IFs, Context IFs and Content IFs respectively [11].

1) Human IFs: These factors are related to human aspects and the usage of technology. This group covers the demographic and socioeconomic background of the end users. This also describes the emotional and physiological states of users.
2) System IFs: This group of factors describes the technical aspects of using a service or application. These factors contain network related e.g., wired, wireless, jitter, bandwidth, and packet loss. These factors also have information related to the de-vice, for example, the display, resolution, and codec supported.
3) Context IFs: The context factors are related to the user's environment and physical location. This group also contains information on temporal, social, economic, task, and technical characteristics.
4) Content IFs: These factors contain information related to the content of the service provider. The content IFs are associated with the video format, encoding, resolution, duration, motion patterns, type, and content of the video displayed.

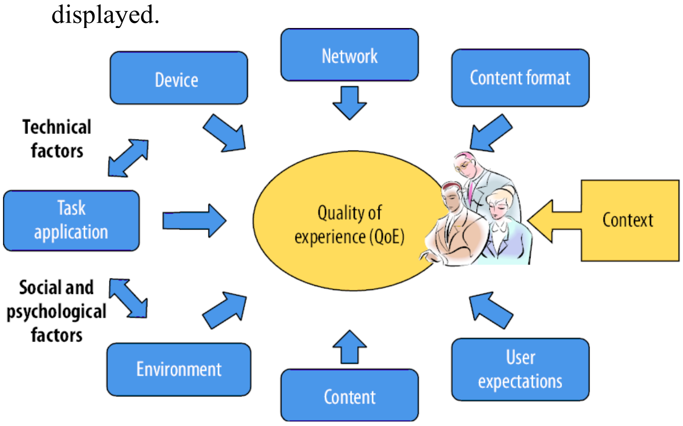

Fig. 1. Quality of Experience [12]

B. Assessment Methodologies in QoE

There are approaches available to measure QoE [13]. The two main categories of approaches are classified as subjective and objective [14]. The subjective approach is considered the user feedback to estimate the video quality as perceived by users. The objective assessment approach, on the other hand, uses mathematical models and statistics methods that provide quality scores that closely resemble the perceived video quality. The detail of assessment methodologies is shown in (Figure 2).

1) Subjective evaluation

In the subjective evaluation method, the experiments were carried out in a lab environment. The TV and mobile phone mediums are used to run videos [15,16]. The Mean opinion score (MOS) is a metric used to evaluate videos. The quality scale ranges from 1 to 5. [17]. There are three categories in which videos are displayed to observers. These are single stimulus (SS) [18], double stimulus (DS) [19], and comparison stimulus [18].

Single stimulus: In a single stimulus, the distorted videos are displayed one by one and rated by each tester. Sometimes, the reference videos are shown without informing the testers. There are three main methods in this category called absolute category rating (ACR), absolute category rating with hidden reference (ACR-HR), and single stimulus continuous quality evaluation.

Double stimulus: In this method, reference videos and distorted video are shown to the tester. To evaluate the distorted video, the tester is asked to consider the difference in quality compared to the reference video. The double stimulus class methods are DSIS, DSCQS, and SDSCE.

Comparison stimulus: In comparison, the stimulus method distorted videos are displayed to the tester. There are two ways in which quality assessment can be carried out. The first is pair comparison (PC) [20] where the tester must indicate which video and recording quality is better. The second is called stimulus com-parison adjectival categorical judgment (SCAC) [20]. In this method, the tester indicates the quality of the second video compared to the first video.

There are issues in conducting a subjective evaluation. Subjective assessments are time consuming and expensive. Subjective evaluation cannot be used to monitor real-time applications. Using a subjective evaluation approach, only a small number of influence factors can be evaluated due to the limited test duration and test subjects.

C. Objective evaluation

The objective models use mathematical and statistical models to estimate QoE based on QoS metrics. There are established objective quality assessment approaches that are the Peak-to-Noise Ratio (PSNR), Structural similarity metric (SSIM) [21], Mul-ti-Scale Structural Similarity [22], SSIMplus [23], Video Quality Model (VQM) [21], and Natural Image Quality Evaluator (NIQE) [24]. These models proven to perform better compared to PSNR. Most researchers use PSNR, the logarithmic ratio between the maximum value of a signal and the background noise, due to its simplicity to assess video quality. The use of PSNR is useful, especially in real-time systems. There is a heuristic mapping of PSNR to MOS exists, although research work [25] demonstrated that the correlation between PSNR and subjective quality could be decreased if the codec type of content changes, unless otherwise specified, PSNR is a qualified indicator of video quality.

Video streams in HD, full HD, and 4k are becoming popular. The issue is how to store and transmit the high-bandwidth data. Video compression technology enables one to reduce bandwidth demand at the cost of reduced video quality. Video compression technologies have the potential to reduce data volume [26]. However, reducing can cause distortion in compressed videos and impact quality. The purpose of video compression is to efficiently reduce visual data by avoiding loss of visual quality due to compression [27].

Most conventional VQA (Video quality assessment) methods, for example, SSIM [28], PVM [29], VMAF [30] and some other methods are discussed in the articles by [21] and [31-32] the

video quality from the perspective of human perception of signal fidelity.

To achieve a video compression rate with minimum loss of visual data, some algorithms and video coding standards, such as MPEG-1, MPEG-2, MPEG-4, H.263, and H.264/AVC are developed [27] and [33].

Videos are stored and compressed in different coding standards. Hence, the com-pression ratios are different from each other and the impact on video quality is also different.

Videos posted online contained distortion and noise compared to the original videos.

These methodologies are tested in a few typical test videos without showing their generalization power. As the solutions are not generic, they have shown that incorporating content in the VQM computation considerably improves the correlation between subjective and objective quality assessment as well as maintaining a low computational complexity [40], [36], [41] and [39].

There are other issues related to objective video quality models, one of which is the limited evaluation of the state-of-art VQMs. Methods are tested on existing databases with few video sequences, which shows little difference in the scene content [42]. Researcher [21] choose twenty sequences from the database {VQEG} [43]. Researchers [44] and [45] extracted twenty sequences from same database [43].

In another research work [31] researcher chose content from one database [46] to evaluate methodologies. In addition to this, the researcher [47] selected content from two different video quality databases [48] and [49]. In research [50] work 30 contents selected from two different databases [46] and [51].

The contents of those databases are used to compare the performance of the considered VQMs. This quite limited the test samples to draw conclusions.

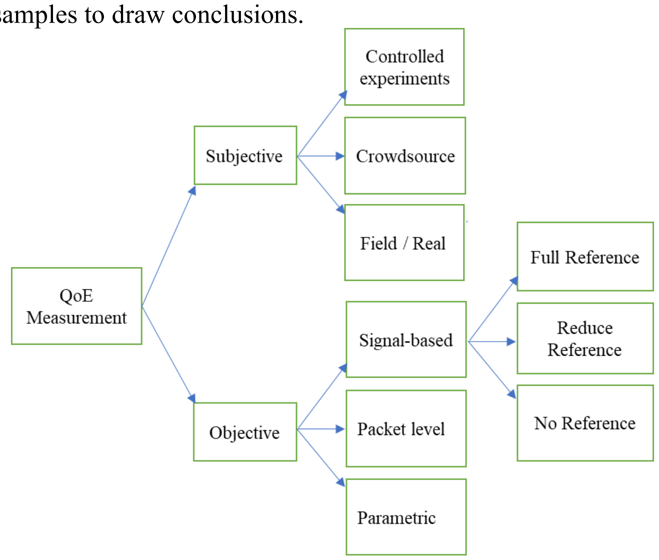

Fig. 2. QoE Assessment Methodology

III. VIDEO COMPRESSION AND QOE

Video streaming requires high bandwidth to stream video. There is a need for compression technologies to compress video. The compression techniques need to compress videos at higher spatial and temporal resolution, dynamic resolution, and quality.

There is a continuous growth in developing compression technologies, from the first international video coding standard H.120 [52], to the latest standards such as MPEG-H.262 [53] and H.264/AVC [54]. There is a recent addition to compression technology called Versatile Video Coding (VVC) [55]. The VVC compresses video by reducing bit rates by 30 - 40 percent compared to the High Efficiency Video Coding (HEVC) standard [56]. The Alliance for Open Media (AOMedia) developed open source codec to compete with MPEG standards. Research work shows that the AOMedia Video 1 (AV1) codec [57] outperforms its predecessor VP9 [58].

The H.264/MPEG-4-AVC [54] is still the most prolific video coding standard, de-spite the fact that H.265/HEVC [56] standard offers better coding performance. A next-generation video coding standard is emerged, Versatile Video Coding (VVC), which targets the coding gain over H.265/HEVC. The VVC standard supports immersive formats (360° video) and higher resolutions, for example, 16K video.

The Alliance for Open Media (AOMedia) develops open-source video codecs. The VP9 standard [58] was developed by Google to be comparable to MPEG and formed the basis for the AV1 standard [57]. The AV1 standard is expected to be the competitor for MPEG standards in the context of video streaming applications.

The performance of video coding algorithms is assessed by comparing their rate-distortion (RD) or rate-quality (RQ) performance on a variety of test sequences. Objective quality metrics or subjective evaluations are utilised to assess the quality of compressed video. The difference in RD and RQ performance between codecs can be calculated using objective quality measurements [59] or SCENIC (subjective assessment) [60]. To compare video codecs and optimize rate vs. quality performance, approach, convex hull rate distortion optimization, is developed by Netflix [61] for adaptive streaming applications.

The research work is focusses on comparisons between MPEG codecs (H.264/AVC and HEVC) and open-source codecs (VP9 and AV1) [62][63][64]. The work also provides details about the application of adaptive streaming services [65][66][61].

IV. VIDEO COMPRESSION TECHNIQUES

In video, transmission, and streaming consist of a large volume of data that need large bandwidth and storage space. The video must be compressed to minimize its storage and transmission capacity. Among several important standards, MPEG-4 is the most used technique for video compression.

1) Motion Picture Experts Group - MPEG-4

The MPEG-4 standards belong to the ISO/IEC/ITU-T family of codecs. The MPEG-4 was initially aimed at low-bit video communication. The MPEG-4 standard is efficient on a variety of bits, ranging from kilobits per second to megabits per second. The MPEG-4 provides improved coding efficiency compared to previous versions like MPEG-2. MPEG-4 can encode mixed media data, for example, video, audio, and speech [67].

2) Advanced Video Coding - MPEG-4 / AVC

Advanced video coding (AVC) is also referred to as H.264 or MPEG-4 part 10. MPEG-4/AVC is based on block-oriented, motion-compensated integer-DCT coding. This standard supports a resolution up to 8K UHD. This standard was created as an alternative to other codecs offering better image quality with higher compression such as MPEG-1 and MPEG-2. MPEG-4/AVC uses advanced encoding techniques and is divided into several pro-files, allowing one to obtain different qualities of the encoded streams in relation to their properties and compression time.

Among the compression profiles, the basic profile (BP) was created, which used in teleconferences and mobile devices, where the stream must be encoded quickly with limited computing power. The second profile is the main profile (MP) used in standard definition (SD) digital broadcasting. The third is high-level profile (HiP) which is used to compress the high definition (HD) streams. The MPEG-4/AVC allows us to compress video streams from 64 kb/s to 960 Mb/s at resolutions from 128 × 96 to 4096 × 2304 [54].

3) High-Efficiency Video Coding - HEVC / H.265

The HEVC standard targets to optimize video resolution performance by incorporating a parallel computing pipeline architecture. This standard aims to increase the aspect of the video resolution with distinct features. Compared to AVC standard, HEVC provides better compression at the same level of video quality. The HEVC supports resolution up to 8192 × 4320 which includes 8K UHD.

AVC uses the integer discrete cosine transform (DCT) with 4 × 4 and 8 × 8 block sizes. High Efficiency Image Format (HEIF) is also based on the HEVC standard. The HEVC standard is the second most used video coding format after AVC [56].

4) Essential Video Coding - MPEG-5 / EVC

The MPEG-5/EVC standards provide better visual quality for video calls and alleviate the expensive royalty for video codecs. This standard defines two profiles. The first one is the baseline profile, which is royalty free as it only consists of technologies that are more than 20 years old, and the second is the main profile which contains enhanced tools to improve the compression efficiency. Both the baseline and main profiles save bit rates 40 % compared to H.264/AVC and HEVC standards [68].

5) Low Complexity Enhancement Video Codec - MPEG-5/ LCEVC

This standard is known as the MPEG-5 (Part-2) standard. This codec is designed to be used with existing video codecs, leveraging specific tools for encoding residuals. This means the difference between the original video and its compressed representation. The LCEVC standard has the ability to improve compression efficiency and reduce computational complexity using a small number of specialized enhancement tools [69].

V. Video Quality Assessment Metrics

There are video quality assessment metrics that can predict user perception when using video services. These metrics are Peak Signal to Noise Ratio (PSNR) [80], Structural Similarity index (SSIM) [81], and Video Multimethod Assessment Fusion (VMAF) [82].

1) Peak Signal-to-Noise Ratio (PSNR)

This is the most common metric used to calculate image and video quality. The PSNR metric is used to compare the codec compression efficiency. To determine the PSNR, first, for a video sequence, the Mean Squared Error (MSE) between each pair i of corresponding reference and processed video frames is:

$$MSE(i) = \frac{1}{WH}\sum_{x=0}^{W-1}\sum_{y=0}^{H-1}\left[Y_r(x,y,i) - Y_p(x,y,i)\right] \quad (1)$$

In equation (1), the values W and H represent the width and height respectively, in pixels. Y_r and Y_p are the luminance values of the reference and processed video frames. Once the MSE is calculated, the $PSNR$ can be computed in decibels for each pair i as follows:

$$PSNR(i) = 10\log_{10}\frac{I^2}{MSE(i)} \quad (2)$$

where I, represent the value of maximum luminance. Now, to find the overall $PSNR$ score for the video, following equation can be used:

$$PSNR = \frac{1}{N}\sum_{i=1}^{N} PSNR(i) \quad (3)$$

In equation (3), N represents the total number of frames in the video. The $PSNR$ is easier to implement, but, on the other hand, $PSNR$ does not always correlate with the end user quality. The two videos perceived qualities may yield a similar score and thus it will not be accurate on the end user persuasion. The $PSNR$ is not aimed at long-term quality predictions. The PSNR metric is designed for quality estimation of video sequences, which is the result of video compression or packet loss.

2) Structural similarity index (SSIM)

The SSIM is a full reference image quality evaluation metric. The SSIM measure image similarity from three different aspects: for example, structure, contrast, and brightness. The range of values for SSIM is [0,1]. If SSIM yields a large value, it means the distortion is smaller. Suppose signal x is the reference frame and signal y is the degraded version, a method is used to compare three components luminance, contrast, and structure. Equation (4) shows the relation between all components.

$$SSIM(x,y) = [l(x,y)]^{\alpha}.[c(x,y)]^{\beta}.[s(x,y)]^{\gamma} \quad (4)$$

In equation (4), the α, β and ◎ represents three parameters. These parameters are used to adjust the importance of each component. The SSIM results would be better if we measure content-dependent distortion. This metric can capture and assess the impact of noise. The SSIM metric is also used to capture blur artefacts. The SSIM is not suited for assessing the quality of super-resolution algorithms. It also does not provide a good result in the case of detecting and capturing spatial and rotational shifts. It will also fail in capturing changes in brightness, contrast, hue, and saturation.

3) VMAF

VMAF is an objective full-reference video quality metric. This metric compares the reference and distorted video sequences to predict subjective quality. This metric combines human vision modelling with machine learning. The VMAF

TABLE I
CODEC IMPLEMENTATION STUDIES

Reference	Codecs	Subjective/objective Methodology	Metrics	Resolutions	Focus of the study
[1]	VVC, SVT, AV1, x265, VP9	Subjective, objective	PSNR, VMAF	Up to 1600p	A comparative study report on bitrate savings
[2]	HEVC and VVC	Subjective	MOS	FHD	VVC performs better than HEVC in terms of compression
[3]	VVC, HEVC, VP9, AV1	Objective, subjective	PSNR, VMAF	Up to 1080p	VVC provides the best coding efficiency. For higher resolutions AV1 outperformed HEVC
[4]	H.265/HEVC, VP9, AV1	Subjective, objective	MOS, PSNR	Up to 1080p	AV1 delivered better values as compared to H.265/HEVC, VP9. AV1 codec take longer to encode
[5]	H.264, H.265, AV1	Subjective objective	PSNR, SSIM, VMAF	1080P	AV1 has shown to result in the best quality for most bitrates and contents considered.
[6]	H.264/AVC, H.265/HEVC VP9, AVS2, AV1	Subjective objective	SSIM plus	4K	AVC shows good quality performance. Limited subjective study
[7]	HEVC	Subjective	VMAF	640 × 416	The VMAF measurements were fitted to the subjective DMOS of expert and non-expert observers using exponential, linear, and logistic curve fitting models
[8]	HEVC, AV1	Subjective objective	PSNR, VMAF	UHD	subjective results confirm that the two codecs do not differ significantly in most cases
[9]	H.264/AVC, H.265/HEVC, VP9	Subjective objective	MOS, PSNR	1080p	H.265/HEVC, VP9 delivers better values as compared to H.264/AVC
[10]	H.264/AVC, H.265/HEVC, VP9, AV1	objective	PSNR, VMAF	Upto1080p	Overall HEVC, VP9 and AV1 perform better than H.264/AVC. Among this, AV1 is having best compression performance

metric is useful for evaluating video quality when comparing video codecs, encoding settings, and transmission standards.

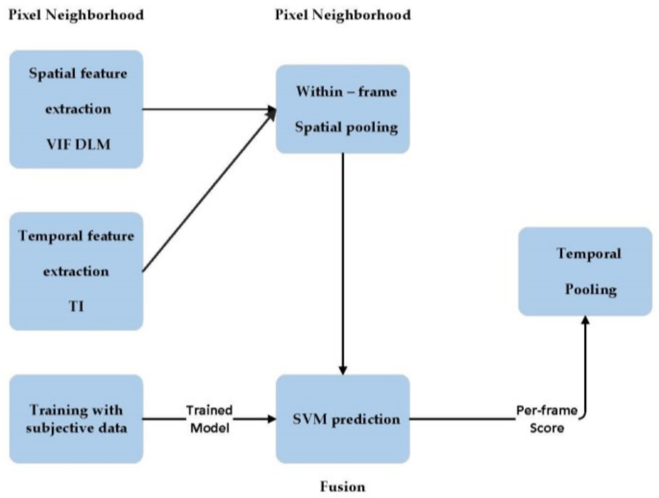

Fig. 3. VMAF Algorithm

The VMAF model combines several video quality features, for example, visual in-formation validity (VIF) [83], detail loss metric (DLM) [84] and also temporal (TI) related information. The VMAF can train support vector machine (SVM) regression on subjective data. The regression results yield per-frame quality score for videos. Figure (3) shows multiple components regarding quality features and integration of other analysis tools into the VMAF model. The VMAF mimics user perception instead of purely objective metrics such as PSNR. The VMAF metric has the capability to capture large differences between codecs and scaling artefacts in a manner that is better correlated with perceptual quality.

VI. Dynamic HTTP Adaptive Streaming (DASH)

In HAS (HTTP Adaptive Streaming) applications video files are encoded at multiple bitrates, resolutions, audio sample rates and representations. The representations will then be divided into segments and stored on an HTTP server. The client sends a request to select segments. This depends on the network conditions which could lead to quality switching and stalling. DASH is one of the most popular streaming technologies for delivering video over the internet. DASH is used by OTT providers like Netflix and YouTube.

A. DASH Data Sets

In this section DASH datasets will be described. The initial dataset [85] contains five video sequences and the segments are based on PSNR objective model. The dataset includes six different segment durations, MPD files and simple profiles. The dataset includes 10 video sequences. The video sequences encoded using four codecs with different segment durations. This dataset is based on service provider recommendations. One issue with this dataset is that recommendations provided by service providers do not consider different client devices.

A dataset [86] developed considering multiple base URLs for all segments. In this dataset video segments provided with MPD files consist of the main and live profile. Another dataset [87] which includes 12 video sequences. The video sequences are encoded using temporal scalability of 6, 12 and 24 fps. The MPD files with the Main profile are provided.

A dataset [88] created for modelling continuous time-varying subjective quality. The video resolution is 720p and of 300 seconds duration. This dataset is based on the quality switching which is performed only using the quality adaptation dimension. This dataset is useful for modeling the continuous time quality varying prediction models.

A dataset [11] consists of 14 source videos and 112 distorted version sequences. The distorted video is compressed version. The dataset only consists of full high definition (FHD) video. The limitation of this dataset is only three source videos, and the distorted version of these videos are provided.

The LFOVIA dataset [90] has 18 raw source videos and 36 distorted versions. This dataset consists of 4K resolutions. Rebuffering and quality switching is taken into consideration measuring video quality.

There is a dataset [91] which includes 24 source videos and 174 distorted versions. The video resolution is 720p and it only considers stalling. This dataset has limitations and is not suitable for designing QoE models. A dataset [92] created consisted of 15 source video and 420 distorted version. The dataset considers four adaptation algorithms. The dataset is useful for measuring client-side adaptation and end user QoE.

B. *DASH Models*

In this section we include the discussion of DASH models. A recent literature focuses on the different types of DASH models.

There are several works focusing on the video quality in MPEG-DASH domain. The research work [93] focuses improving on the video quality of experience (QoE) and considering parameters for the adaptation algorithm. In this work nine objective VQA methods are compared. The objective methods are applied on video sequences containing spatial and temporal activities. The result from the study reveals that more VQA methods require to be utilized in streaming services.

The work [94] carried out which focus on stall events on video quality in HAS application. The media quality and the impact of stall events correlated. The impact of stall and quality switches on the perceived QoE studied. A model from the study is inherited and tested. The study [95] carried out in the video quality and DASH domain. In this study a model is proposed estimating the cumulative video quality for HTTP adaptive streaming. The evaluation results reveal essential components of the cumulative quality model. The results show that the proposed model achieves high prediction performance. The subjective tests [96] were carried out to measure the video and audio quality. The live music over mobile networks with MPEG-DASH is considered. The results reveal that reducing audio quality has an impact on quality of experience (QoE).

This research also provides an objective model for audio and video quality estimation. The research study [97] on video encoding and optimization reveals that adaptive video encoding approach is suited for SVT-AV1 and x25 codecs. The study also reports bitrate savings when tested with VVC, SVT-AV1, x265, and VP9 codecs. A study [98] reports on the influence of segmentation parameters on video quality. The goal of the study was to improve the segmentation process. The results demonstrate enhancement in SSIM values.

The video codecs AV1 and HEVC were compared in adaptive streaming environment [99]. The objective evaluation is carried out with PSNR and VMAF metrics. The study results show there is no significant difference in the perceived quality between AV1 and HEVC.

The database named Waterloo Streaming QoE Database III (SQoE III) is established [100]. The database consists of video sequences created from a variety of sources. The subjective and objective evaluation is carried out. The result of this study provides foundation for developing adaptive video streaming algorithms and video QoE.

In recent research carried out by [101] on segment size selection in video streaming. The tradeoff between video length and segment size is studied. In this study the playback quality is evaluated. The study results reveal segment size can minimize the buffer outage and thus impact the video quality.

The research [102] demonstrates the HTTP push-based approach for video quality of experience. The study is carried out with HEVC codec. The results reveal high video quality and lowering freeze time. This approach reduces delay as compared to other approaches like HTTP/1.1.

VII. Open Challenges

In this paper, we presented a brief review of video quality of experience (QoE) assessment methods and techniques. The subjective and objective assessment methods are reviewed thoroughly. Video compression technology is used to compress the high-definition videos and its essential for video transmission. Different compression techniques and coding strategies reviewed and discussed. A variety of codecs presented in the study mainly developed by MPEG and Google.

There are many factors which potentially impact the video quality. The encoding parameters, quality switching and stalling are some important factors covered in literature. The research [103] consider stalling patterns and quality level switching. In this work the author measure the impact of stall events on the video quality. The researcher [104] correlated content quality and the impact of stalling on the video quality of experience (QoE).

In this paper, QoE assessment methodology and compression technologies are also reviewed. It is observed that most of the existing work has limitations. There are many studies that considers low resolution video streaming. Limited studies available considering Full HD and UHD (4K) content. The codec implementation is also limited in terms of video streaming [5-6][8]. Only a few studies considered video codec technology in video streaming. Most studies implement MPEG H.264 and H.265 codecs [33][55]. There are other codecs which need to be considered. There are limited investigations on the parameters that have the potential to affect video quality. For example, the quantization parameters should be considered. Subjective studies are required to determine any other important factors that can impact the video quality of experience [105-106].

Potential factors which possibly affect video QoE should be investigated and thus optimisation models should be formed. The Quantization parameters (QP) are important factors.

Existing studies have limited approaches to consider Quantisation parameters and investigate it thoroughly [107].

MPEG-5 has two parts, Part-1 is Essential Video Coding (EVC) and Part-2 is LCEVC. The EVC codec is desirable to address the business needs of an organization, particularly video streaming. There is a high demand for capabilities in terms of compression ratio, as new formats such as UHD, 4K, and 8K are introduced. The enhanced technologies High Dynamic Range Video (HDR) and High Frame Rate (HFR) and service scenarios like Virtual Reality also come into existence. The MPEG-5, Part 2, Low Complexity Enhancement Video Coding (LCEVC) is designed in a way for improving compression and minimizing overall computational complexity. As the LCEVC uses base and enhancement layers, it saves bits. The LCEVC is useful for sports broadcasting as it reduces the amount of data without compromising quality of the videos. The LCEVC is also effective in e-learning. As LCEVC reduces bandwidth consumption while using the internet at home [108-110].

The challenge faced by the researchers in adaptive streaming QoE is the evaluation methods. There is limitation choosing between subjective and objective evaluation methods. There are limited databases available which are particularly focusing on adaptive streaming. For example, the database [85] which is focusing contains five video sequences and the segments are based on only PSNR objective model. The database [89] created which consists of full high definition (FHD) video sequences. The issues with these databases are limited availability of original and distorted version video sequences. There is a need to evaluate video quality over adaptive streaming applications. Very few studies are available to exploit the objective quality models. The research [98] work evaluate quality using SSIM model. The work [99] demonstrate video quality using PSNR and VMAF models.

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