Video Quality Assessment Methods: A Bird's-Eye View

P. M. Arun Kumar, S. Chandramathi

***Abstract*—**The proliferation of multimedia technology and services in today's world provide ample research scope in the frontiers of visual signal processing. Wide spread usage of video based applications in heterogeneous environment needs viable methods of Video Quality Assessment (VQA). The evaluation of video quality not only depends on high QoS requirements but also emphasis the need of novel term 'QoE' (Quality of Experience) that perceive video quality as user centric. This paper discusses two vital video quality assessment methods namely, subjective and objective assessment methods. The evolution of various video quality metrics, their classification models and applications are reviewed in this work. The Mean Opinion Score (MOS) based subjective measurements and algorithm based objective metrics are discussed and their challenges are outlined. Further, this paper explores the recent progress of VQA in emerging technologies such as mobile video and 3D video.

***Keywords*—**3D-Video, no reference metric, quality of experience, video quality assessment, video quality metrics.

I. Introduction

IN recent years, rapid development of digital video technology have resulted in broad applications in the areas of video teleconferences, Video-on-Demand (VoD), digital camera, IPTV, video transmission over wireless networks and so on. The delivery of video streams through heterogeneous network environments and variety of devices justifies the need for the better quality evaluation scheme and framework to enhance the overall user experience.

Various stages of video signal processing results in degradation of digital video and henceforth the requirement of methods and metrics to evaluate the video quality becomes highly critical. Traditional QoS (Quality of Service) focuses only on network performance by considering parameters such as bandwidth, delay, jitter, and packet loss [1]. In QoS, human subjectivity (user perception) is not taken into account and hence a novel term called Quality of Experience (QoE) that focuses more on perceived quality is introduced.

International Telecommunication Union (ITU) defines QoE as "The overall acceptability of an application or service as perceived subjectively by the end user" [2]. Precisely measuring QoE factors for different multimedia services is quite complex and challenging as it includes technical, economical and human factors [3]. Hence QoE extends the concept of QoS from measurement of accuracy in network data delivery to multimedia quality of user perception [4]. Video QoE is measured through subjective and objective methods.

Arun Kumar P M is with the Information Technology Department, Hindusthan College of Engineering and Technology, Coimbatore, Tamilnadu, India (e-mail: arunkumarpm@gmail.com).

Dr. S. Chandramathi is with Sri Krishna College of Technology, Coimbatore, Tamilnadu, India (e-mail: chandrasrajan@gmail.com).

This paper is organized as follows: Section II discusses subjective quality assessment methods to evaluate video quality in reliable way. The method involves human observers evaluating the video quality through Mean Opinion Score (MOS). Objective video quality assessment that provides algorithmic assessment of video quality is introduced in Section III. Section IV discusses the assessment of newly emerged visual signals (3D/Mobile videos). Certain concluding remarks are highlighted in Section V.

II. Subjective Video Quality Assessment

Subjective Quality Assessment provides the most fundamental and reliable method to assess the video quality by the judgment of human evaluators. In subjective quality assessment, experts (typically 15 to 30 members) will watch the assigned video clips and quality of videos are rated according to their perception. The average rating over all the subjects (experts or viewing members) for a given video clip is termed as Mean Opinion Score (MOS) [5].

Due to involvement of human views and expectations, the variability of viewer ratings becomes inevitable. Yet the subjective assessment methodologies provide the rules and regulations to be followed during the process of video quality assessment in reaching substantial accuracy. Also the experts are trained vigorously before attempting the video quality tests to ensure better results. ITU has recommended various direct scaling methods for subjective testing [6], [7].

This method requires checking of viewing conditions such as screen distance and position to ensure perfect environment for the assessment. The observer's room conditions such as lighting, seating positions are checked. Before evaluating the videos, the human observer's count and skillset for that particular evaluation is verified.

Various settings are deployed during subjective evaluation. (i) Single or Double Stimulus method: in Single Stimulus evaluation, only impaired sequence shown to the subjects, whereas in Double Stimulus method both reference and impaired video are taken for evaluation. (ii) With or without repetition: as the subjective evaluation may prolong for longer periods, the experts may get exhausted and hence repetition of the test can be initiated if required. (iii) Type of Scale: subjective study deploys scaling methods such as quality scale, impairment scale, comparison scale and numerical scale.

Subjective quality assessment is formulated by absolute or comparison method, continuous or discrete methods. The most common methods for such evaluation are categorized and given in Table I.

For all the methods in Table I except DSCQS, the ratings provided by the experts are averaged to achieve Mean Opinion Score (MOS). The mean of differential subjective scores is calculated as Differential Mean Opinion Score (DMOS) in DSCQS method. ITU-R Rec BT .500 provides procedures and rules to be followed in subjective testing for television whereas ITU-T Rec. P. 910 recommendations is applicable for advanced multimedia applications.

The quality of multimedia is assessed accurately by various subjective test and they provide basic framework for any objective quality metric. The need of plenty of human resources, the time consumption for the assessment makes subjective methods impractical and cumbersome. As this method is unsuitable for real time applications, an appropriate objective Video Quality Assessment (VQA) metric is required to evaluate video quality as perceived by an average human observer [8].

TABLE I
SUBJECTIVE VIDEO QUALITY ASSESSMENT METHODS

S.No	Method	Description
1	Double Stimulus Impairment Scale (DSIS) [ITU-R Rec.BT.500-11]	The reference and test video are shown only once. The experts rate the amount of impairment in a discrete 5 level scale with a range from very annoying to imperceptible. Degradation Category Rating (DCR) recommended by ITU-T Rec.P.910 is a method similar to DSIS.
2	Double Stimulus Continuous Quality Scale (DSCQS) [ITU-R Rec.BT.500-11]	Pair of videos comprising reference video and test video is presented twice. A continuous quality scale of 0-100 ranging from bad to excellent is used.
3	Absolute Category Rating (ACR) [ITU-T Rec.P.910]	The observer will watch the test video without any reference. It is a single stimulus method that uses discrete 5 level scale (bad to excellent). ACR-HR (Hidden Reference) provides a variation of ACR.
4	Stimulus Comparison (SC) or Pair Comparison (PC) [ITU-T Rec.P.910]	The test videos from the same scene but different conditions are paired and the experts make judgement for each pairs.
5	Single Stimulus Continuous Quality Evaluation (SSCQE) [ITU-R Rec.BT.500-11]	The observers view video clip of small duration. Using a slider, the experts provide continuous judgement on perceived quality.
6	Simultaneous Double Stimulus for Continuous Evaluation (SDSCE) [ITU-R Rec.BT.500-11]	Two parallel screens are used by the observer and the quality testing is done by comparing reference and impaired video.
7	Subjective Assessment Methodology for Video Quality (SAMVIQ) [ITU-T Rec. BT.1788]	The assessment video is played back according to the subject's need and pace and the rating will be given instantaneously.

III. OBJECTIVE VIDEO QUALITY ASSESSMENT

Objective quality metrics are algorithms formulated to emphasize the quality of the video and predict the viewer MOS. For the analysis of decoded video, the objective VQA can be classified in to three types namely, Data Metrics, Picture Metrics and Packet or Bit Stream based metrics.

A. Data Metrics

This metric measures the fidelity of the signal without taking its content into account. Video quality metrics viz. Mean Squared Error (MSE) and Peak Signal to Noise Ratio (PSNR) have been used extensively in video processing research for a long time due to its vast recognition. Fast computation and easy implementation make these metrics a popular choice among the video researchers.

PSNR provides approximate relationships with the video quality perceived by human observers as it is based on Byte by Byte comparison of data without considering what they actually represent. Spatial relationship of pixels and human visual system differences are ignored by this metric [5].

Fig. 1 depicts the difference in perceived quality of two images though they have the same PSNR. This is due to the properties of human visual system. Data metrics, as elucidated by the above images are distortion agnostic and content agnostic in nature [5]. MSE provides better evaluation of the global quality measured objectively, but being statistical based metric, it has poor correlation with perceived quality measurements. Thus these metrics provide the measure of lost packets and incorrect bits but not the perceived quality of the video.

(a) (b)

Fig. 1 Images with identical PSNR, yet with different perceived quality

B. Picture Metrics

This metric predicts the video quality by considering the information based on video content and distortion. There are two types of picture metrics namely Vision Modelling and Engineering Approach [9]. Vision Modelling Approach adopts HVS (Human Visual System) and hence results in improved correlation between subjective and objective video quality evaluation. Though this method is too hard to understand completely, it provides better prediction of perceived video quality. The critical parameters such as color perception, contrast sensitivity and pattern masking are considered during evaluation.

Table II summarizes few metrics that are grouped under vision modelling approach. In Engineering Approach, extraction and analysis of various artifacts of the video is performed. The critical features may include contours and blockiness, blur induced by compression / transmission system. The engineering approach follows top-down methodology and mainly focus on distortion analysis. Table III lists the most important engineering metrics for video quality assessment. Picture metrics can also be classified into perceptual oriented and natural visul characteristics oriented metrics which is illustrated in Chikkerur et al. [26]. The major sub-classification of those metrics is portrayed in Fig. 2.

C. Packet and Bit Stream Based Metric

For applications such as internet streaming that applies video delivery over IP networks, the network loses on video quality should be calculated by a novel metric. Packet and bit stream based metric provides this feature by observing the packet header information and the encoded bit stream directly without considering full decoding of the video. The limitation of the metric is that it is specific to selected codec and network protocols.

TABLE II
VISION MODELLING APPROACH METRICS

S.No	Metric	Author (s)	Description
1	First Image/Video quality metric.	Mannos and Sakrison (1970) Lukas and Badrikis (1982)	Distortion measure for monochrome still image [10]. Filtered error measure provides better prediction of picture quality [11].
2	Visual Differences Predictor (VDP) [12]	S.Daly (1993)	Prediction of visible differences between two digital images
3	MPQM (Moving Picture Quality Metric) [13]	Van den Branden, Lambrecht et al (1996)	The quality metric for digitally coded video and it considers spatial and temporal aspects of HVS.
4	Sarnoff JND (Just Noticeable Differences) [14]	J.Lubin and D.Fibush (1997)	Depends on known properties of vision and formulates according to psychophysical data.
5	Perceptual Distortion Metric (PDM) [15]	Winkler et al (1999)	Distortion metric for color video sequences and it is based on contrast gain control model of HVS
6	Wavelet based VSNR metric [16]	Chandler et al (2007)	Based on rear threshold and suprathreshold properties of human vision, the visual fidelity of natural images are observed.
7	Foveated Mean Squared Error (FMSE) [17]	Mano Vranjes et al (2010)	Variable resolution of HVS across the visual field.
8	Motion based Video Integrity Evaluation (MOVIE) metric [18]	Seshadrinathan et al (2010)	Integrates both spatial and temporal aspects of distortion measurement (Spatial MOVIE and Temporal MOVIE)
9	Perceptual Quality Index (PQI) [19]	Zhao et al (2011)	Multiple visual properties considered for better result.

TABLE III
ENGINEERING MODEL APPROACH METRICS

S.No	Metric	Author (s)	Description
1	Color Image Quality metric [20]	Winkler et al (2004)	Specific spatial and temporal artifacts such as blockiness and blur are considered
2	Structural Similarity Index (SSIM) for video [21]	Wang et al (2004)	Uses structural distortion as an estimate of perceived visual distortion. Uses mean, variance and covariance of original and distorted sequences.
3	Video Quality Metric (VQM) [22]	M.H. Pinson et al (2004)	Extraction of perception based features and shows exceedingly good performance.
4	VVIF (Video Visual Information Fidelity) [23]	H.R.Sheikh et al (2005)	Video statistics combined with HVS modelling.
5	Multiscale SSIM (MS-SSIM) for video [25]	Z-Wang et al	Extension of SSIM and is applied to video.
6	Speed SSIM [24]	Z-Wang et al (2007)	SSIM combines with statistical models of visual speed perception.

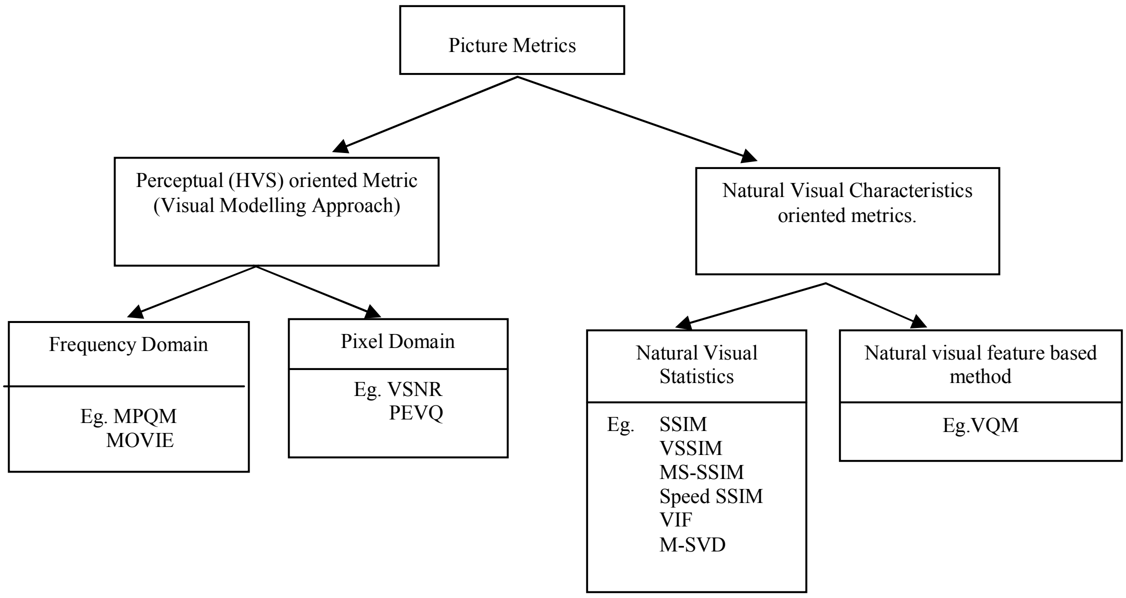

Fig. 2 Classification of Picture Metrics [26]

D. Hybrid Metrics

It uses a combination of packet information, bit stream or even decoded video. Examples of packet and bit stream based metrics are proposed by Verscheure et al [39] and Kanumuri et al. [40]. V factor quality metric is also an example of hybrid metric [5]. The classification of hybrid metics (adapted from ITU-T) is shown in Fig. 3.

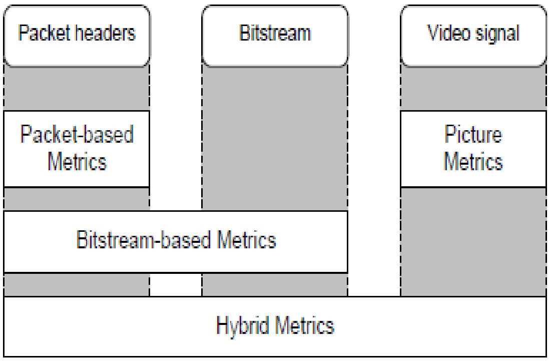

Fig. 3 Hybrid Metrics [5]

LIVE (Laboratory for Image and Video Engineering) is the freely available public database containing distorted videos and subjective scores to rate the Objective VQ Metric [27]. Other databases used are ECVQ and EVVQ [8]. VQEG is the common forum to validate OVQA models through ITU recommendations. According to ITU standards, objective quality assessment can be categorized to five models depending on the input data type as in Table IV.

TABLE IV
CLASSIFICATION OF OVQA BASED ON TYPE OF INPUT DATA [28]

S.No	Layer	Input data to predict QoE
1	Media layer model	Video signal
2	Parametric Packet layer	Packet header information
3	Parametric Planning	Quality planning parameters for networks
4	Bit stream layer model	Encoded bit stream information
5	Hybrid Model	Combination of 2 or 3 above models

The media layer objective quality assessment model can be classified into Full Reference (FR), Reduced Reference (RR) and No Reference (NR) metric. These three metrics are based on the availability of information about the reference video. The representation of these metrics is shown in Figs. 4-6.

E. Full Reference (FR)

It operates on frame by frame comparison between the reference video and the test video. The complete reference video in unimpaired and uncompressed form is needed for the assessment. Also precise spatial and temporal alignment of the two videos is expected and henceforth makes it impractical in real time applications. MSE/PSNR and HVS based metrics belongs to Full Reference methods. The application area of FR Metric relies in offline video quality measurements such as codec tuning or lab testing.

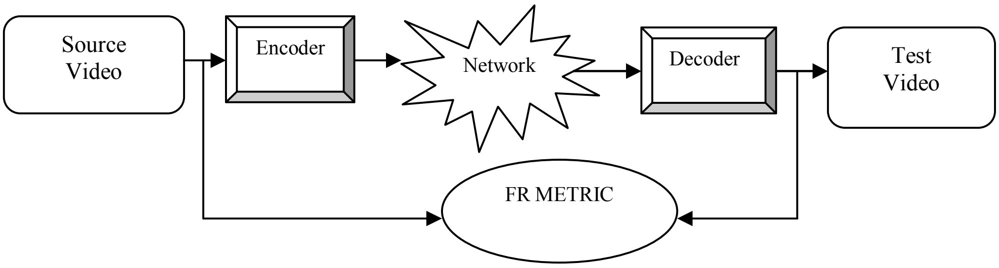

Fig. 4 Full Reference Metric [41]

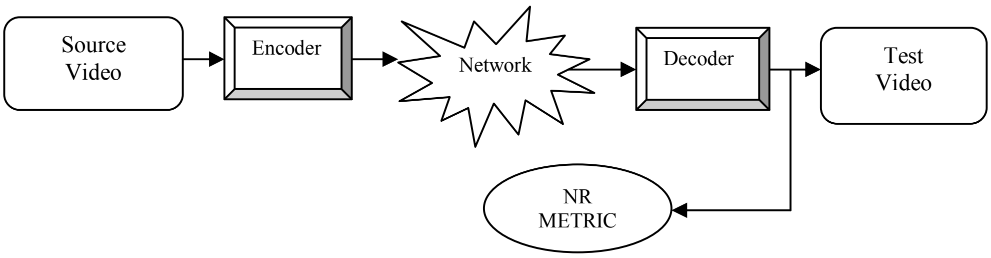

Fig. 5 No Reference Metric [41]

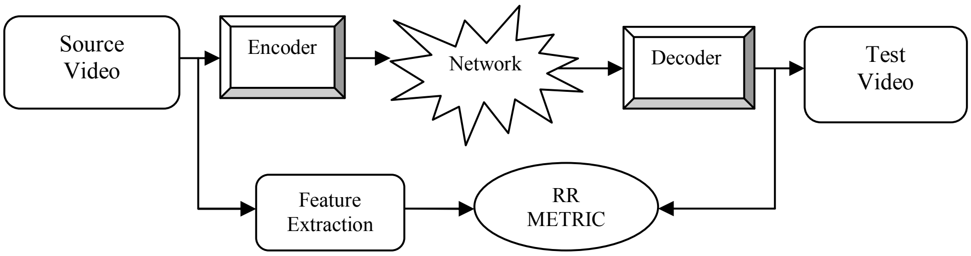

Fig. 6 Reduced Reference Metric [41]

This metric aims to provide accurate video analysis while processing. The extensive study of FR Metric based on model based Perceptual Video Quality Metric (PVQM) and signal driven PVQMs resulted in two advanced quality estimation techniques based on impairment decoupling and machine learning approaches [29].

F. No Reference (NR)

No Reference metric observes only the test video without any reference video. Such metric provides more flexibility than FR metric and also completely free from alignment issues. NR metric always make assumptions about the video content and distortions. NR Metrics are applicable for monitoring of in-service video system that demands real time measurements.

Due to unavailability of reference video, this metric can be used anywhere in an existing compression and transmission process. The well known approaches in NR Metrics include Blockiness Estimation and Blur Measurement.

G. Reduced Reference (RR)

This metric extract critical features and comparison of the reference and test video is performed by considering only those features. RR Metric has the advantage of limited alignment requirements but still it relies on back channel access to reference video.

Objective video quality evaluation can also be classified as Out-of-Service and In-Service methods. Out-of-service or Offline video quality measurement applies a Full Reference model that is suitable for multimedia laboratory testing, where foolproof quality analysis is mandatory [26]. The In-Service systems are applicable for real time environment such as video streaming.

RR Metrics can be classified as image distortion modelling, modelling HVS and based on natural video statistics [29]. The commonly used metrics to evaluate the performance of objective video quality metrics are Pearson Correlation Coefficient (PCC), Spearman Rank Order Correlation Coefficient (SROCC), Outlier Ratio (OR) and Root Mean Square Error (RMSE) [26].

IV. VIDEO QUALITY ASSESSMENT FOR MOBILE AND 3D VIDEO

Mobile phones are used extensively now a days and due to rapid increase in mobile network capacity, video traffic on such handheld devices gain significance. When video is transported over wireless network, the video stream is subjected to quality degradation due to modification entrusted by content delivery networks, cellular operators and also because of errors during compression and transmission [30].

In video over wireless networks, visual perception through Human Visual Systems (HVS) will provide more accurate results and hence Subjective Video Quality Assessment (SVQA) can be deployed and also perceptual optimization of wireless video networks provides new research paradigm [31].No Reference video quality measurement is more suited for video delivery over mobile devices. Transmission factors such as low bit rate, low resolution in error prone networks impose limitations and hence the video quality is impaired by several artifacts. The major artifacts related to mobile video are spatial coding artifacts, temporal artifacts and artifacts based on packet loss [32].

Video blockiness, video blurriness and video noise are major spatial domain distortions that affect mobile videos. Small blocks of single color lead to artifacts in the images of mobile video termed as blockiness [33]. The viewer may notice this impairment as one large pixel displayed over a large area. Severe blockiness hampers the mobile video quality and may lead to extreme user dissatisfaction. Hence blockiness issue is critical to enhance QoE of mobile video users.

Blurriness is due to the impairment in high frequency components during compression process. Due to insufficiency of bandwidth, the video cannot be encoded properly and so the blurriness effect is resulted due to fast moving scenes. Video noise is a random dissimilarity of gray or color values in the images of a video generated by various devices or process [33]. Various analog noises that creeps into videos includes (i) Radio channel artifacts such as high frequency interference and video reduplication, (ii) VHS artifacts such as color specific degradation, chaotic line shift at the end of the frame etc., (iii) Film artifacts such as dust, dirt, spray, scratches and fingerprints.

Typical digital noise impairments include blocking, ringing etc. Ringing is a shimmering effect around high contrast edges. Blocking belongs to low bitrates artifacts. Video freezing, video jerkiness and video blackout are other critical video quality issues in mobile video [34]. Various video noise reduction methods based on spatial video and temporal video (Motion adaptive, Motion compensative methods) are adopted [38].

3D/Stereoscopic cinema, television, gaming and various 3D portable devices have gained greater implications in today's world. However exploring the Quality of Experience of 3D videos is complex and multidisciplinary problem [29]. Improved QoE is an important aspect in understanding human visual perception of 3D multimedia for developing better 3D quality metrics. Factors such as depth perception, immersion and naturalness should be taken into account for 3D video quality assessment. Major 3D artifacts include keystone distortion, puppet theater effect, crosstalk, cardboard effect, sheer distortions and disocclusions [35].

Several algorithms have been developed to extract 3D information from 2D image using depth map. Transmission and storage of 3D video processed by a novel method called Multi View Coding (MVC) which is an extension of H.264. Conversion from 2D to 3D / format conversion are critical steps exclusively applied for 3D video transmission process [36].

3D video quality assessment can be classified as subjective assessment, physiological assessment and performance assessment techniques [37]. Subjective assessment evaluates the quality of content by observing the expert opinions. Double Stimulus Continuous Quality Scale (DSCQS), Absolute Category Rating (ACR), Simulator Sickness Questionnaire (SSQ) and Visual Analogue Scale (VAS) are the methods deployed for subjective study of 3D videos. Physiological methods calculate the comfortness of the subjects/experts by estimating brain activities such as fMRI, EEG or by monitoring medical parameters such as heart rate, breathing, eye blinks, etc. The performance assessment provides performance inference of the experts (score, response time, etc.) in completing a specific work. A typical performance assessment model is carried out by Advanced Trail Making Test (ATMT).

V. Conclusion

The advancement in multimedia is envisioned to progress with various critical challenges and novel ideas as a result of technologies and new applications in this digital era. This paper highlights the classification of video quality assessment methods based on subjective and objective measures. Various video quality metrics, their usage in telecommunication networks and implications are reviewed. Quantifying the quality of video by new concept called Quality of Experience provides ample scope and boundless opportunities to explore recent advances in multimedia-aware systems in emerging networks. The paper affirms that the reliability and efficiency of various objective video quality methods solely depends on the closeness of correlation with subjective measures. The advancement in video QoE and the inherent challenges during quality evaluations is paving way for greater significance in video coding fraternity. Henceforth, the QoE aware multimedia can be applied to numerous research niceties related to next generation novelties such as mobile and 3D video.

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