

A Survey on 360° Video: Coding, Quality of Experience and Streaming

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Abstract

The commercialization of Virtual Reality (VR) headsets has made immersive and 360° video streaming the subject of intense interest in the industry and research communities. While the basic principles of video streaming are the same, immersive video presents a set of specific challenges that need to be addressed. In this survey, we present the latest developments in the relevant literature on four of the most important ones: *(i)* omnidirectional video coding and compression, *(ii)* subjective and objective Quality of Experience (QoE) and the factors that can affect it, *(iii)* saliency measurement and Field of View (FoV) prediction, and *(iv)* the adaptive streaming of immersive 360° videos. The final objective of the survey is to provide an overview of the research on all the elements of an immersive video streaming system, giving the reader an understanding of their interplay and performance.

Keywords: Video streaming, Virtual Reality, Quality of Experience

1. Introduction

Over the past few years, the commercialization of Virtual Reality (VR) headsets and cheaper systems using smartphones as viewports [1] have fueled a strong research interest in 360° immersive videos, and the technology is currently un-

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5 dergoing standardization [2]. Commercial Head-Mounted Displays (HMDs) are currently being sold by multiple companies, and the artistic potential of the new medium is being explored for both gaming and movies.

This kind of technology has the potential to make video a more intense experience, with a stronger emotional impact [3], thanks to the wider Field of
10 View (FoV) and the direct user control of viewing direction. 360° videos also have a huge potential for storytelling, as multiple story lines can be developed in parallel [4]. Immersive video also has the potential to enhance empathy and participation in news stories [5], although evidence regarding its use shows mixed results [6]. Psychological factors such as perception of embodiment [7]
15 also affect immersiveness [8], particularly when an avatar is animated in the VR simulation [9].

Immersive video streaming presents some unique challenges [10], especially for live streaming: since the full omnidirectional view is wider than traditional video, it requires far more bandwidth to be streamed with a comparable quality.
20 In order to reduce the throughput of 360° streams [11], tile-based solutions have become a standard: the sphere is divided in several tiles, according to a pre-defined projection scheme, and each tile can be downloaded as a separate object. In this way, clients can concentrate most of their resources on the tiles that are in the user's FoV, i.e., the ones that will actually be displayed with the
25 highest probability, resulting in the same Quality of Experience (QoE) even if tiles outside the viewport have a very low resolution or are not downloaded at all. Naturally, this kind of solution requires an accurate prediction of where the user's gaze will fall, which is in itself a complex research topic. The design of the tiling scheme is also a significant factor in both the compression efficiency
30 of the video coding scheme and the final QoE of the user.

Additionally, the geometric distortion [12] generated by the projection of spherical omnidirectional video onto a flat surface reduces both the accuracy of traditional QoE metrics and the efficiency of 2D video codecs. Since traditional QoE metrics are designed for planar images and videos, their direct use does
35 not correctly represent the human perception of the video and is only loosely

correlated with actual QoE. The design of projective corrections for legacy metrics and 360-specific ones is an active area of research. Cybersickness [13] is another major problem for immersive video streaming, requiring both a more precise metric to evaluate quality variations and better streaming techniques to
40 reduce stalling.

The distortion issue also affects automatic saliency estimation, which can help predict the FoV, and even feature extraction and Convolutional Neural Networks (CNNs) [14] are affected by it, requiring *ad hoc* corrective methods [15].

This survey aims at providing readers with a broad overview of the state of
45 the art in all the major research directions on omnidirectional video. We give a full perspective on the building blocks of an omnidirectional streaming system:

- In Sec. 2, we examine coding methods, discussing different standards and projections and how they can introduce different kinds of distortion and enable more efficient compression;
- 50 • In Sec. 3, we describe subjective and objective metrics to evaluate the QoE of omnidirectional videos, and why it is a complex challenge;
- In Sec. 4, we examine the question of saliency and FoV prediction. We review empirical approaches based on user behavior, analytical ones based on image features, and joint ones that consider both past viewpoint direc-
55 tions and the current image;
- In Sec. 5, we present the state of the art on omnidirectional video streaming techniques, focusing on tiling-based approaches. We also review some recent network-level innovations to provide support to omnidirectional streaming.
- 60 • In Sec. 6, we present a summarized version of the lessons learned on each topic and conclude the paper with a discussion of the open research challenges in the field.

Each section of the paper includes a discussion of the key challenges and open problems in the field.

65 A number of recent surveys, whose contribution is summarized in Table 1,
have examined the state of the art on different topics in the field. One work [16]
focuses on projection, explaining several state of the art methods in detail and
evaluating them on a public dataset with known quality metrics. The authors
explore viewport-adaptive coding as a possible solution to the demanding band-
70 width requirements of omnidirectional video, and briefly mention the possible
sources of coding distortion, which are examined in detail in [17]: this work
considers the steps of the encoding chain, examining how each one introduces
different kinds of local and global image distortions. A more recent work [18]
takes a broader view, examining the existing QoE evaluation metrics, along with
75 viewer attention models for eye and head movements, while the networking as-
pects of streaming, from resource allocation to caching, are reviewed in [19].
Finally, a survey focusing on system design and implementation [20] examines
some of the existing systems, protocol and standards for acquisition, compres-
sion, transmission, and display of omnidirectional videos.

80 These recent works only present a limited review of FoV-adaptive stream-
ing, while our Sec. 5 has a more extensive review of the existing literature.
Furthermore, while all of these works concern themselves with QoE, this work
is the first to provide an analysis of the existing comparisons between objective
metrics, resulting in insights for further research and implementation. Finally,
85 these recent surveys only present a limited review of FoV-adaptive streaming,
and none of them has a complete perspective that unifies evaluation and stream-
ing: since the efficiency of adaptation techniques strongly depends on both the
encoding techniques and the FoV, presenting them in a unified manner is im-
portant to get a full picture of the design requirements. The discussion of the
90 field developed in this survey has a unified perspective, linking the later sections
to the earlier ones and proposing some ideas for a holistic development of 360°
streaming systems.

Table 1: Summary of the existing surveys on omnidirectional video

Survey	Year	Topic
Recent advances in omnidirectional video coding for virtual reality: Projection and evaluation [16]	2018	Projection
Visual Distortions in 360-degree Videos [17]	2019	Visual distortion
State-of-the-Art in 360° Video/Image Processing: Perception, Assessment and Compression [18]	2020	Saliency, QoE
Network Support for AR/VR and Immersive Video Application: A Survey [19]	2018	System implementation
A Survey on 360° Video Streaming: Acquisition, Transmission, and Display [20]	2019	Protocol design

2. Coding, compression and distortion

The efficient encoding of omnidirectional video has all the well-known issues of 2D video encoding, with an additional degree of complexity: since filters and coding tools are often based on 2D images, the spherical content needs to be projected to a flat surface to be processed and encoded. In this section, we discuss the different factors that should be considered when encoding omnidirectional video, presenting the main projection schemes and coding solutions, both in the spatial and temporal domains.

2.1. Projection and tiling

The geometric distortion issue in 360° video is the same that cartographers have faced for thousands of years when drawing maps of the Earth [21]: projecting a sphere onto a planar surface inevitably leads to some form of distortion. However, projection is not the only source of distortion, as the omnidirectional video processing pipeline can cause it at every step [17]. The first one is the acquisition of the image: omnidirectional images and videos are usually stitched from multiple cameras [22], and this can introduce several kinds of issues at the edges. These can range from missing information and misalignment of the edges to differences in the exposure and “ghosting”, and are often particularly strong at the poles, which most camera systems cannot capture and are often reconstructed in post-processing. Video can also have temporal discontinuities, such as objects appearing and disappearing or warping as objects move close to the stitching areas [23]. In order to avoid smoothness issues and increase the

115 coding efficiency, appropriate motion models that explicitly use rotation need
to be used [24].

After the omnidirectional image has been acquired, it needs to be converted
to a planar representation for encoding and storage. It can then be divided into
tiles to allow tile-based streaming, which we will discuss in detail in Sec. 5. The
120 warping patterns generated by the combination of the map projection and tile
edges will then interact. Consequently, the form and severity of the geometric
distortion effects depend strongly on the projection and tiling scheme, which is
crucial for efficient compression of omnidirectional video.

The Equirectangular Projection (ERP) [25] is the oldest, simplest, and most
125 common projection for omnidirectional video: it is similar to the *plate carrée*
geographic projection, as it divides the sphere of view in a number of rectangles
with the same solid angle. Distortion at the poles makes projection wasteful, as
it encodes the poles with more pixels than the equator: as viewers usually focus
their attention close to the equator, the poles are often outside the FoV.

130 The dyadic projection [26] tries to solve the pole oversampling issue by
reducing the sampling for vertical angles above $\frac{\pi}{3}$ from the equator, while the
barrel projection [27] encodes the top and bottom quarters of the ERP as cir-
cles, reducing the number of pixels used for the two caps. The polar square
projection [28, 29] is another adaptation that works like the barrel projection,
135 but maps the poles to two squares. There are other techniques to compen-
sate for the pole oversampling issue: the equal-area cylindrical projection [30]
reduces the height of the tiles with the latitude, while the latitude adaptive ap-
proach [31] adapts the number of tiles to the latitude. The result is also known as
Rhombic Mapping (RBM) [32], since the tiles are arranged in a rhombic shape,
140 which can then be rearranged onto a rectangle. The octagonal projection [33]
does the same with a rough latitude quantization, resulting in its namesake
shape. Nested Polygonal Chain Mapping (NPCM) is another downsampling
technique [34], which starts from the ERP output and linearly approximates
the optimal sampling density.

145 The Cubic Mapping Projection (CMP) is the other projection to be widely

Table 2: Summary of state of the art projections

Projection	Geometry	Main advantages and issues
Equirectangular [25]	Each rectangle has the same solid angle	Oversampling at the poles
Dyadic [26]	Equirectangular with reduced polar sampling	Distortion at the poles
Barrel [27]	The sphere is mapped to a cylinder	Distortion at the edges
Polar square [28]	Barrel-like, mapping the poles to squares	Distortion at the poles
Equal-area cylindrical [30]	Equirectangular with latitude-dependent tile height	Reduced polar oversampling
Latitude adaptive [31]	Equirectangular with latitude-dependent number of tiles	Reduced polar oversampling
Rhombic mapping [32]	Similar to latitude adaptive, arranging tiles in a rhombus	Efficient retiling
Nested polygonal chain [34]	Downsampling from equirectangular	Reduced polar oversampling
Cubic mapping [35]	Projection from sphere to cube	Higher efficiency, lower polar distortion, edge distortion
Equiangular cubic mapping [39]	Equiangular mapping on cube faces	Reduced face edge distortion
Other solids [41, 42, 43]	Projection on solids with more faces	Lower projection distortion, higher edge distortion
Variable tile shape [44]	Tiles can be adapted to the content	Low distortion, complex encoding and decoding
Rotated sphere [45]	Baseball-like unfolding	Increased coding efficiency, low edge distortion
ClusTile [46]	Viewer behavior-based adaptive sampling	Low distortion, complex encoding and decoding

adopted. It constructs a cube around the sphere [35], then projects rays outward from the center. Each ray intersects with a single point on the surfaces of both solids, resulting in the projection mapping. The CMP [36] is more efficient than the ERP in terms of compression [37], and is currently used by Facebook
150 for omnidirectional videos [38]. A comparison between the ERP and CMP projections is shown in Fig. 1. It is easy to see that distortion at the poles is far lower, while objects close to the edges and corners of a face are more distorted. This should be intuitive, as the cube mapping approximates a sphere better close to the center of each face: this effect can be mitigated by applying equiangular
155 mapping to the cube faces [39], or in general by adjusting the sampling to privilege the center of each face [40].

Solids with a larger number of faces, such as octahedrons [41], rhombic dodecahedrons [42], or icosahedrons [43], can reduce the effect of edges by having a lower stretch and area distortion, like the Sinusoidal Projection (SP) [47],

160 which is an equal area projection. However, there is a trade-off when choosing the number of faces: polyhedrons with more faces have a lower projection distortion, but a higher number of discontinuous boundaries. An example of octahedral projection is shown in Fig. 2. Other less regular projection shapes are also possible, with tiles of variable size and shape [44]. The Rotated Sphere
165 Projection (RSP) [45] unfolds the sphere under two rotation angles and stitches them like a baseball; this can be obtained from the ERP, and it can increase coding efficiency.

Finally, a more advanced approach to projection integrates content and viewer behavior in the design [48]: areas that have salient content and are often
170 watched will be sampled at a higher rate. ClusTile [46] is another projection that uses past viewer behavior, designing a set of tiles that minimizes bandwidth requirements for past views. A framework evaluating the projections presented above was described in [14], and some results comparing the basic projections' compression efficiency and distortion with H.264 and H.265 codecs are presented
175 in [49], finding that the equal-area cylindrical projection outperforms both the ERP and CMP. The main projection methods we presented in this section are summarized in Table 2.

Offset projection is a concept meant to save bandwidth and exploit the available knowledge of the user's viewing direction: offset projections use more
180 pixels to encode regions close to the predicted gaze direction, while regions at wide angles from it have a higher compression. The Truncated Square Pyramid (TSP) [50] projection constructs a truncated pyramid around the sphere, with the bottom facing the same way as the viewer. The projection is then constructed like the CMP. The construction of the solid is shown in Fig. 3, in
185 which two truncated pyramids with different settings are shown: the one on the right has a smaller upper base, giving more relative importance and more pixels to the region facing the viewport directly. When the pyramid's upper base is very small, regions at wide angles from the user's expected gaze are encoded by very few pixels [51], with extreme compression gains.

190 The Offset Cubic Projection (OCP) [52] adopts another way to perform off-

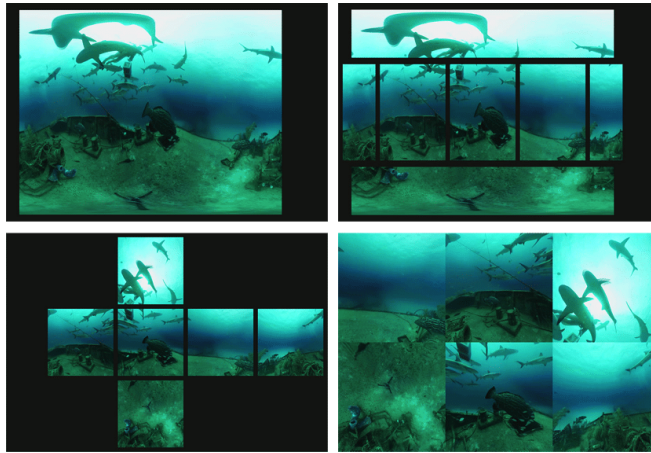


Figure 1: Equirectangular and cubemap projection comparison. The figure was adapted from the Facebook video engineering blog: <https://engineering.fb.com/video-engineering/under-the-hood-building-360-video/>

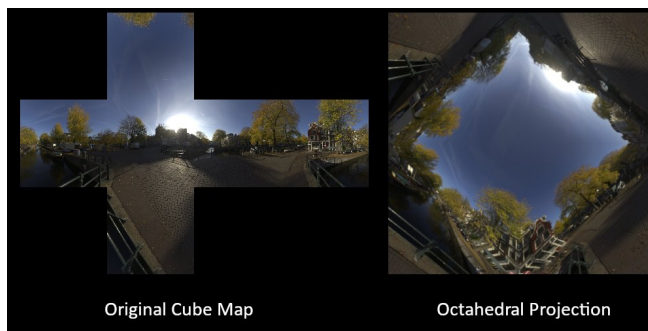


Figure 2: Equirectangular and octahedral projection of the same scene. Image credits: Omar Shehata, <https://omarshahata.me/>

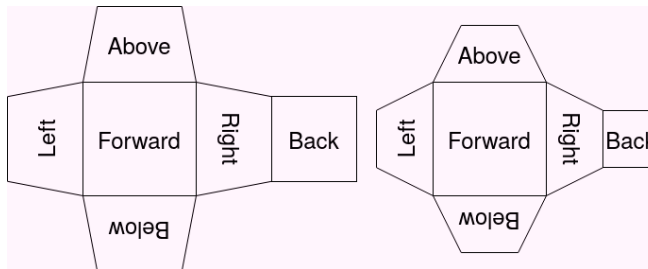


Figure 3: Truncated square pyramid projection with different settings.

set projection: it is a version of the CMP, with an offset that distorts the sphere before projecting it to the six cube faces. In the resulting frame, views in one direction have a higher pixel density than in other directions. The same concept can be applied to any combination of the equirectangular and barrel projection, and a possible option is to consider only an offset on the horizontal plane. Offset projections can significantly improve the QoE of an omnidirectional image, as long as the view orientation is close to the offset. Another offset projection is the asymmetric circular projection [53], which decreases sampling density in the area outside the FoV smoothly by using a circle with a center closer to the surface in the direction of the user’s gaze. In this way, there are no explicit seams. If an FoV prediction is available, streaming clients can select the appropriate offset orientation and increase QoE without a corresponding throughput increase [16]. The same operation can be performed for the equirectangular and barrel projection. An evaluation of the quality of different offset projections is available in [52], for different viewing angle errors and offset distortion settings.

2.2. Compression and encoding

There are a number of competing video encoding standards being developed [54]: the most popular are High Efficiency Video Coding (HEVC) [55], or H.265, and AOMedia Video 1 (AV1) [56], but the older Advanced Video Coding (AVC) [57], or H.264, is still widely used. Additionally, Versatile Video Coding (VVC) [58], the future H.266, promises to add new capabilities to the existing standards. The 2D encoding techniques in the standards are highly optimized and close to ubiquitous, and most omnidirectional streaming systems reuse the 2D coding pipelines [59]. However, all the distortion issues discussed in Sec. 2.1 do not just impact the QoE of the projected and encoded video, but also the coding efficiency. Furthermore, the resampling and interpolation steps of the encoding pipeline often cause aliasing and blurring, and if these steps are not managed carefully [60] they can also introduce visible seams and combine with the projection scheme to create distortion. While older works can get good results using custom techniques on the spherical image, often without projec-

tion [61], most of the recent literature follows the standard approach, with all its advantages and pitfalls. The decision on the representations that need to be encoded and stored [62] in a streaming system can affect the requirements on bandwidth support, server storage space and distortion.

225 Naturally, coding efficiency depends on the projection used, and it is possible to optimize coding for a certain projection, reducing its downsides and increasing compression performance. Since ERP oversamples the polar regions, it is possible to use smoothing [63] or reduce the accuracy of motion vectors and the coding block resolution [64] as a function of the latitude, increasing
230 the coding efficiency with minimal QoE impacts. Another way to compensate for this distortion is to adaptively set the Quantization Parameters (QPs), using the Weighted to Spherically Uniform PSNR (WS-PSNR) weights: regions that are less important in the metric will be encoded with a rougher compression [12]. The same optimization can be performed for other metrics, such as
235 Sphere-based PSNR (S-PSNR) [65]. A more advanced way to set the QPs is to combine the geometric information with the saliency [66], privileging the salient areas which will be watched more often.

The ERP latitude-adaptive quantization technique is adopted in [67], combined with some steps to terminate the coding unit partition early in these areas,
240 speeding up the encoding process. Early coding unit termination can also be performed in a content-dependent way [68], computing the local texture complexity. Another optimization for ERP concerns the edges of the image: since the left and right edges are actually continuous, the coding unit parameters need to be set to avoid visible seams [69]. In [70], the region-adaptive quantization
245 scheme is combined with an adaptive mechanism that reduces the frame rate to increase picture quality if the motion in the content is not too fast. An alternative strategy is rotation: since regions close to the equator have less distortion, interesting regions of the image with high motion and fine-grained textures can be rotated to the equator, while the less interesting regions are rotated to the
250 poles and have more distortion [71]. This approach is extended in [72], using a CNN to predict the orientation that maximizes the achievable compression over

the Group of Picture (GoP), as both content and motion vector discontinuities can affect the compressibility.

Filters are another important concern in omnidirectional coding, as their effectiveness relies on proper adaptation to the projection. In [73], the Sample Adaptive Offset (SAO) filter that can improve coding quality for sharp edges is adapted to the ERP, reducing the coding complexity by up to 80% with no QoE impacts. A correction to the standard HEVC deblocking filter can reduce the CMP edge distortion [74] by aligning the face edges with the filter edges, filtering only the left and top borders to maintain rotational symmetry, and using the correct pixels in the 3D representation for the filter decision-making. A similar approach is used in [39], limiting the coding unit splits at the face edges and adapting the HEVC filter to the equiangular CMP by enforcing the face boundaries and using the correct pixels. The authors also adapt a CNN denoising filter to the projection. Coding unit depths can also be adapted to the content and CMP geometry, reducing coding time significantly [75].

In projections with more irregular face shapes, the inactive samples that are used to pad the 2D projected frame to a rectangular shape can be ignored in the rate-distortion optimization, resulting in further compression benefits [76]. A full coding system using a sampling-adjusted CMP is presented in [77], including padding and other techniques to limit face boundary discontinuities such as packing, i.e., reshuffling of the cube faces in the representation so that contiguous objects in the 3D sphere are close in the projected image.

2.3. Motion estimation and temporal coding

The temporal element is critical when encoding omnidirectional video: since the content is dynamic and encoded in GoPs, considering the motion in subsequent frames significantly increases the compression efficiency. The first example is downsampling: performing the operation on each frame statically does not achieve the same compression efficiency as considering the quality of the dependent B and P frames [78] when downsampling the independent I frames they are tied to. It is also possible to reduce the number of independent frames

by adopting the Shared Coded Picture (SCP) technique, which introduces P-coded pictures that are the same across all representations. This enables longer GoPs, increasing the efficiency of the code, but also the encoding and decoding
285 complexity [79].

Motion estimation is inextricably tied into saliency, which we will discuss in Sec. 4: the content that is most important to viewers, and on which their gaze usually fixates, is often also the fastest-moving one. This has important consequences for streaming systems which use prediction of the future FoV to
290 optimize the bandwidth utilization, as these systems require accurate predictions and efficient coding. As the use of offset projection, temporal coding, and FoV-oriented predictive streaming all aim at improving compression while maintaining an accurate representation of moving content, the interplay of these subsystems must be considered when designing a streaming system.

The effects of projection also complicate motion modeling in omnidirectional
295 video: since projection is a non-linear transformation, a simple translational motion of all the projected pixels in a local block (like in the HEVC standard) will not be able to capture the actual motion of the content. This distortion can become catastrophic if the motion crosses face boundaries, causing texture discontinuities that seriously impair QoE.
300

A possible solution is to reproject the motion vector: if the motion on the sphere is translational (i.e., the movement is on the surface of the sphere), the motion vector on the projected video is converted to the spherical motion vector, which is then interpolated [80]. In this way, the coding efficiency and
305 the QoE increase; the same can be done for purely rotational motion. This technique was proposed for the CMP [35, 39] and ERP [24], integrating it with standard HEVC motion modeling schemes. In [81], a general model is tested for ERP, CMP and octahedron projections. The spherical coordinate transform can be used to further improve performance and extend the possible motions
310 to the whole 3D space [82], working in spherical coordinates and using relative depth to convert between ERP and the 3D space. It is also possible to assign different motion vectors to pixels in the same block, correcting the motion vector

distortion [83]. A less efficient but less computationally demanding way to correct motion vectors in ERP is to exploit the WS-PSNR [84] weight map to
315 calculate a scaling factor for the motion vectors [85].

Another technique deals with distortion due to motion compensation failures at face boundaries extends a face by linearly projecting the pixels in the other faces [86] to preserve texture continuity [87]. This operation can be performed more efficiently using polytope geometry [88]. Another work [81] considers the
320 angle of the block in the sphere in the ERP projection when computing the padding.

Deep learning is a new alternative to traditional motion estimation: in [89], CNNs are used to reconstruct future cubemap frames, combining the encoded P or B frame with the last received I frame. This scheme can improve Peak
325 Signal to Noise Ratio (PSNR) without increasing the required bandwidth.

3. Quality of Experience in Immersive Videos

QoE is the ultimate measure of performance for both standard and panoramic video streaming. However, its subjective nature makes finding a general metric to measure it extremely difficult [90]. Although most of the research on stan-
330 dard video is still applicable, 360° video presents some unique challenges [91]: an important factor in the perceived quality of panoramic video is the geometric distortion given by the projection of the spherical image on a planar display [92], which is more pronounced with wide FoVs. It is possible to assess these distortions objectively [93], but not their impact on QoE. For a more comprehensive
335 survey on the possible sources of distortion in 360° videos, we refer the reader to [17]. Another important factor in the quality of omnidirectional video is the mosaic technique, which can generate distortion in dynamic scenes [94].

In this section, we consider subjective and objective methods to measure omnidirectional video QoE, and present the wide body of literature on the eval-
340 uation of these metrics. We conclude the section with a discussion of dynamic effects on omnidirectional video QoE.

3.1. Measuring QoE: subjective methods

QoE is a complex concept, as it involves the human interaction with the content, and its automatic assessment is a challenging problem [95]. Since a direct
345 measure of QoE requires human subjects, the assessments need to be performed in controlled and replicable conditions. The standard methodologies for conducting these assessments are specified by the International Telecommunication Union (ITU) in [96], and distinguish between Absolute Category Rating (ACR) and Degradation Category Rating (DCR) scoring. The standard methodologies
350 were developed for 2D video, and they often have to be adapted for omnidirectional video: in [97], an example of a new ACR methodology for omnidirectional video without requiring users to take off their HMD is presented. The standard testing conditions specified by the Joint Video Exploration Team (JVET) [98] are also often used, although slightly different from the ITU recommendations.

355 The golden standard for ACR quality assessment is Mean Opinion Score (MOS): the content is shown in controlled conditions to a large number of human subjects, who then rate it on a scale from 1 to 5. When evaluating compression schemes, Differential Mean Opinion Score (DMOS) is often used as a DCR metric, evaluating the difference between the quality of the compressed content
360 and the original's: this is a fundamental step of the evaluation of new coding schemes, for both standard and omnidirectional content [99]. Omnidirectional video content is even more challenging, as static image quality is not the only component that influences QoE, and even subjective studies need to consider FoV changes and how the different encoding of foreground and background
365 affects the experience [100]. A testing methodology that considers the dynamic aspect of QoE, accounting for delays between user motion and the high-quality rendering of the video in the new direction, is presented in [101].

Double Stimulus Impairment Scale (DSIS) is another way to measure quality impairment of compressed sequences specified in [96]: instead of rating the content
370 QoE on an absolute scale, and possibly comparing it with the unimpaired version's score, this assessment method asks users to rate the degradation directly, after being shown the original and impaired sequence one after the other.

Table 3: Available subjective QoE assessment datasets

Reference	Type	Subjects	Videos or images	Total sequences
[109]	Video	221	60	600
[110]	Video	88	6	48
[97]	Video	30	6	60
[111]	Video	30	13	364
[112]	Video	30	10	60
[113]	Static images	20	16	320
[114]	Video	21	5	75
[100]	Video	12	3	24
[115]	Video	27	2	10
[116]	Video	13	10	150
[117]	Video	23	16	384
[118]	Video	340	30	1608
[119]	Stereoscopic video	30	13	364

However, this method may cause cybersickness more often [102] when used for omnidirectional video. A more complete comparison between various assessment methods is presented in [103].

Immersiveness is another factor that needs to be considered in omnidirectional video QoE assessment, as the quality of the video can significantly improve the sense of presence in a VR environment. In order to do so, more factors than just picture quality need to be considered, as audio quality and spatial features can have a strong impact on sense of presence, as well as the proprioceptive matching between the user’s movements and the video displayed on the HMD [104]. Multi-sensory environments [105] that include haptic feedback or even smells present yet more challenges: in [106], immersiveness is evaluated when an external sensory stimulus is combined to the omnidirectional video, finding that this kind of addition can improve immersiveness and enrich user experience.

Finally, an interesting development that straddles the line between subjective and objective metrics is the creation of metrics based on objective physiological data from the user collected by smart watches and other simple sensors [107]. In [108], the authors develop a QoE metric based on the combined electroencephalographic, electrocardiographic and electromyographic signals, achieving high correlation with MOS.

Several QoE studies have published their datasets, providing a common base

for future research on QoE assessment. The largest dataset is the one presented
395 in [109], with 221 total subjects watching 60 video sequences, following the
methodology described in [110], which also presents a public dataset with a
total of 88 subjects watching 48 video sequences extracted from 6 videos. The
dataset presented in [97] contains data from 30 users watching 60 sequences, and
it was obtained using different methodologies, so it can be used to compare them.
400 In [111], 13 videos are processed into 364 sequences, watched by 30 subjects.
In [112], 10 omnidirectional videos of 10 seconds each are evaluated by 30 non-
expert subjects. The dataset in [120] uses static images, having 20 subjects
evaluate 528 compressed versions of 16 base images, as does the one in [113],
with 320 compressed versions of 16 images watched by 20 subjects. The authors
405 of [114] also released their dataset, with 21 participants watching 75 impaired
video sequences with different resolution and compression levels. There are other
small-scale datasets associated to other measurement studies [100, 115], while
two more large dataset, with 13 subject watching 150 videos and 23 subjects
watching 384, were presented in [116] and [117], respectively. To the best of our
410 knowledge, the largest available dataset was presented in [118], and is divided in
5 scenarios with an approximately uniform division of samples. Finally, there is
a large-scale dataset for stereoscopic omnidirectional video, which was presented
in [119]. The datasets above are summarized in Table 3.

3.2. Objective QoE metrics

415 The easiest method to objectively measure the QoE of an omnidirectional
image is to directly use a classic 2D metric such as PSNR, Structural Similarity
Index (SSIM) [121], Multiscale SSIM (MS-SSIM) [122], Visual Information Fi-
delity in Pixel Domain (VIFP) [123], or Feature Similarity Index (FSIM) [124].
However, these metrics do not take the geometric distortion caused by the pro-
420 jection of the spherical image into account; indeed, most objective QoE metrics
for omnidirectional images and videos are adaptations of these metrics, with
some corrections for the geometrical distortion resulting from the projection of
spherical images on a plane.

S-PSNR [98] is an adaptation of PSNR that takes a number of uniformly distributed sampling points on a spherical surface, then reprojects them on the reference and distorted omnidirectional images and computes PSNR. Points that are between sampling positions in the 2D plane are mapped to the nearest neighbor. WS-PSNR [125] takes the opposite approach, computing PSNR on each pixel of the projected image, then weighting the results proportionally to the area occupied by the pixel on the sphere. PSNR for Craster Parabolic Projection (CPP-PSNR) [126] is a projection-independent adaptation of PSNR; it applies a Craster parabolic projection that preserves areas in the spherical domain, then calculates PSNR on the resulting image. By virtue of being independent of the projection used in the image, it allows the comparison of different projection methods. Finally, Spherical SSIM (S-SSIM) [127] and Weighted to Spherically Uniform SSIM (WS-SSIM) [128] are adaptations of SSIM to the spherical domain: the structural similarity is adjusted to compensate the geometrical distortion using a weighting function similar to the one used by WS-PSNR. In [114], the sphere is divided into patches using a Voronoi diagram, and the 2D algorithms are applied on the patches, reducing the distortion.

The content itself can be the basis of the weighting system, as in [99]: Content Preference PSNR (CP-PSNR) and Content Preference SSIM (CP-SSIM) are adaptations of the two metrics that take the viewport direction and content saliency into account, using a predictive model to gauge future viewing direction. However, saliency and eye movement models are not always perfect, and using the center of the viewport as a proxy for gaze direction is still very imprecise [129].

More complex metrics take into account several factors, often combining the objective metrics mentioned above: in [130], a non-linear Perceptual Video Quality (PVQ) model is derived, starting from SSIM and other metrics and matching them to a predicted MOS. The same operation is performed by the Normalized Quality versus Quality factor (NQQ) model in [131], which computes QoE as a non-linear function of a combination of coding parameters such as spatial resolution and quantization factor, whose parameters are derived from

455 the spatial activity in the image and the low-order moments of the luminance distribution.

Learning tools can also be used to estimate these models: in [132], Back Propagation (BP) is applied on inputs on multiple scales, considering single pixels, regional superpixels, salient objects, and the complete projection, resulting in the Quality Assessment in VR systems (QAVR) metric. Generative Adversarial Networks (GANs) are another learning tool that can be used to train neural networks to estimate QoE, and the Deep VR Image Quality Assessment (DeepVR-IQA) [133] metric is based on them. GANs involve two neural networks in opposition to each other: as one network is trained to estimate the QoE, the other’s objective is to generate examples that trick the other into estimating an incorrect quality. This improves training convergence and can increase overall correlation with subjective test scores. The metric in [109] includes head and eye movement data in the learning process, concatenating patch-level CNNs with a fully connected network to obtain the QoE score. CNNs can also be used to determine 3D omnidirectional video quality [113], with additional preprocessing. The Viewport-based CNN (V-CNN) model combines viewport prediction with a CNN [134]: the QoE for different viewports is computed by the CNN, while another spherical CNN predicts possible future viewports’ viewing probability and determine the weights of their contribution to the expected QoE. Table 4 presents a summary of the main full-reference QoE metrics presented in this section, along with the references of the comparison studies they appear in.

No reference metrics can measure QoE in different context, in which no uncompressed image is available. Metrics such as the Natural Image Quality Evaluator (NIQE) [140], based on natural image statistics, and the Six-Step Blind Metric (SISBLIM) [141], which is the combination of six different distortion measurements, have good performance on 2D images and videos, but the only study to check their effectiveness for immersive video [111] has found that their performance is significantly affected by the geometric distortion, making them only weakly correlated with subjectively perceived quality. The Multi

Table 4: Summary of the main presented objective QoE metrics

Metric	Description	Comparison studies
PSNR	Pixel-level Mean Square Error (MSE) over the whole image (2D)	[84, 98, 126, 135, 133, 99, 136, 132] [137, 124, 131, 111, 127, 114, 112, 120, 138]
SSIM [121]	Structural similarity on a small scale (2D)	[130, 99, 133, 124, 131, 114, 111] [132, 127, 112, 120, 138]
MS-SSIM [122]	Structural similarity on multiple scales (2D)	[137, 133, 124, 131, 111, 114, 120, 138]
VIFP [123]	Shannon model measuring shared information (2D)	[137, 133, 131, 120]
FSIM [124]	Feature-based model	[124, 120]
S-PSNR [98]	PSNR on sampling points from a sphere remapped on the 2D projection	[98, 99, 139, 135, 133, 132] [114, 136, 137, 111, 127, 112, 109, 138]
WS-PSNR [84]	PSNR weighted proportionally to pixel area on the sphere	[84, 99, 139, 114, 135, 133] [136, 137, 131, 111, 127, 112, 109, 138]
CPP-PSNR [126]	Compares quality across projection methods with equal area projection	[126, 139, 99, 114, 135] [133, 136, 137, 111, 127, 112, 109, 138]
S-SSIM [127]	SSIM with corrections for projective distortion in the spherical domain	[127]
WS-SSIM [128]	SSIM weighted proportionally to pixel area on the sphere	[128]
Voronoi [114]	SSIM and PSNR on Voronoi patches	[114]
CP-PSNR [99]	Saliency- and viewport-weighted PSNR	[99]
CP-SSIM [99]	Saliency- and viewport-weighted SSIM	[99]
PVQ [130]	Non-linear function of SSIM	[130]
NQQ [131]	Non-linear function of the coding parameters	[131]
QAVR [132]	Learning-based model based on features at multiple scales	[132]
DeepVR-IQA [133]	Adversarial generative model to learn QoE	[133]
Model in [109]	Learning-based metric with head and eye movement input	[109]
V-CNN [134]	CNN on viewports weighted by viewing probability	[134]

Channel 360° Image Quality Assessment (MC360IQA) metric [142] is a no reference metric using a multi-channel CNN on the six faces of a cube, trained on the dataset in [111]: the metric outperforms even 2D full reference metrics on the dataset.

490 3.3. Evaluating QoE metrics

The conditions for testing QoE metrics in immersive video are specified by the JVET in [98]; a wider discussion on the framework [139] also provides some reference experiments, with objective and subjective quality metrics; it also introduces the *evil viewport* problem. Evil viewports correspond to FoVs in which

Table 5: Performance of the main presented objective QoE metrics. The table should be read horizontally: the metric in each row is compared to one for each column. Metrics whose rows have more green cells are more closely correlated with subjective MOS

	PSNR	SSIM	MS-SSIM	VIFP	WS-PSNR	S-PSNR	CPP-PSNR
PSNR		Worse	Worse	Worse	Worse	Worse	Worse
SSIM	Better		Similar	Worse	Better	Better	Slightly better
MS-SSIM	Better	Similar		Worse	Better	Better	Slightly better
VIFP	Better	Better	Better		Better	Better	Better
WS-PSNR	Better	Worse	Worse	Worse		Slightly worse	Slightly worse
S-PSNR	Better	Worse	Worse	Worse	Slightly better		Slightly worse
CPP-PSNR	Better	Slightly worse	Slightly worse	Worse	Slightly better	Slightly better	

495 the discontinuous edge caused by the stitching of images from different cameras is clearly visible; it is important to consider evil viewports as a separate case, as QoE metrics that take the whole sphere into account might underestimate their impact on QoE because of the relatively small area of the stitching edge. Furthermore, another study [143] argues that short videos should not be used
500 for QoE evaluation in VR, as users' attention takes longer to focus in this kind of environment. A detailed evaluation of the JVET database, with subjective experiments, is presented in [112].

In recent years, several studies have compared objective quality metrics to measure their correlation with actual subjective QoE: due to the strong de-
505 pendence of the correlation between objective metrics and MOS on the actual content of the images, tests performed on different datasets often have contradictory results, and the wide variation across videos of the same dataset confirms that the effect is fundamental and not due to experimental design. The subjective experiments in [136], for example, show no advantages of the
510 360-specific PSNR-based metrics over the baseline 2D metric; however, this contradicts the results in [135, 112], which both find that CPP-PSNR has better performance than the other metrics, and S-PSNR and WS-PSNR also outperform standard PSNR. All of the works above [135, 136] confirm that MOS decreases sharply if the resolution is lower than 1920p; since only part of the

515 video is inside the viewport at any time, even 1080p video has a low perceived resolution. All later studies confirm that standard PSNR is worse than any other quality metric, but they often include other metrics, such as SSIM [121] and VIFP [123]. In [137, 120, 131], VIFP significantly outperforms SSIM, MS-SSIM and WS-PSNR, which achieve a similar performance, while PSNR does
520 even worse. Similar results are reported in [127], which includes S-SSIM but not VIFP or MS-SSIM; the 360-specific SSIM variant outperforms both its 2D ancestor and the PSNR-based metrics. The most complete study, which includes several less common 2D QoE metrics and SSIM flavors, finds that SSIM outperforms both MS-SSIM and the various PSNR-based metrics. The results of the
525 various experimental studies are summarized in Table 5, which compares all the algorithms that are present in at least two of the works presented in this section. The table should be read horizontally: in each row, the corresponding metric is compared to the others (one in each column), and a qualitative summary of the comparison is given by the cell color. The row corresponding to VIFP, for
530 example, is completely green, showing that it does better than any other metric in the studies in which it is examined, while PSNR’s row is entirely red. An interesting case is presented by the comparison between SSIM and MS-SSIM, whose relative performance is similar, but with a very high variance: MS-SSIM performs better on some datasets [137], but worse in others [111], and neither
535 is clearly better in others [131]. Another work [138] compares the basic metrics’ performance and complexity, and finds that most are well-correlated to MOS in the studied scenarios. The experiments by the authors show that the more complex methods in [130, 131, 109, 132, 133] have a higher performance than traditional metrics, but they have not been corroborated by independent studies
540 yet.

The results of the analyses and comparisons are summarized in Table 5, with a color-coding scheme to give the reader a first-glance impression of the metrics.

3.4. *Dynamic factors in video QoE*

The dynamic nature of video is also a major factor in QoE that should be
545 taken into account: as in 2D video streaming, stalling events [144] can signif-
icantly affect both the perceived quality of 360° videos [145] and the sense of
presence of the experience [115]. Since omnidirectional video is more bandwidth-
intensive than standard video of the same quality, and buffering is limited by
the accuracy of FoV prediction, as we will discuss in detail in Sec. 5, avoiding
550 rebuffering events is likely to be a major issue in bitrate adaptation algorithm
design.

Quality fluctuations also have an impact on QoE, and omnidirectional video
can have two sources of picture quality variation: as in all adaptive video stream-
ing systems, the bitrate adaptation algorithm can change the quality to adapt
555 to the connection, either decreasing it if the available bandwidth does not sup-
port the current quality level or increasing it if there is unused capacity. The
second cause of quality fluctuations is specific to omnidirectional video: as we
will discuss in Sec. 5, streaming systems transmit regions outside the predicted
viewport at a lower quality to save bandwidth, which causes sharp decreases in
560 QoE when the user turns and the lower-quality content is displayed.

The impact of quality variations due to FoV changes in adaptive systems
is modeled in [146], using quotients between exponential functions of the qual-
ity variation rate to approximate the subjective quality when fluctuations are
present. This model is extended in [118], which considers a more complete
565 model for several different possible scenarios and tests it on a large-scale sub-
jective evaluation dataset. Naturally, a more precise model of the trajectory of
the user’s gaze could improve the accuracy of these QoE models, tying quality
evaluation, encoding, and FoV tracking inextricably.

Another study [147] investigates the impact of head turn movements on sub-
570 jective QoE, finding that these movements can have a strong impact on perceived
quality. However, the effect of user movements on the QoE of omnidirectional
video is still largely unexplored, and should be investigated further. Another
interesting issue, which is explored in [148], is the impact of audio degradation

on omnidirectional video QoE: the authors use a neural network to combine the
575 effects of video and audio impairment, training it on a subjective assessment
dataset.

Immersive videos with fast camera motions are also subject to cybersick-
ness [149], which is caused by a mismatch between perceived motion and visual
input. Cybersickness symptoms often include oculomotor disturbances, nausea,
580 and disorientation, and they are strongly dependent on the content [13]: immer-
sive scenarios with strong pitch motion such as rollercoaster rides or parachute
dives can induce far stronger symptoms than more horizontal scenes. The tech-
nical challenges of designing immersive systems are explored in more detail
in [150, 105].

585 Gaming is another important application of VR, and the definition of QoE
can be slightly different in this context, as both enjoyment and performance need
to be taken into account. Immersive gaming is affected both by the quality of
the video and by other factors such as the control scheme [151], which should
include the headset movement input: measurement studies have been performed
590 in different contexts, such as driving simulators [152], first-person shooters [153],
sport simulators [154], or even training simulators [155].

4. Saliency and FoV tracking

Saliency is the quality that makes part of an image or video stand out and
capture viewers' attention [156]. In this section, we discuss how to evaluate
595 saliency in omnidirectional videos, then apply the concepts to FoV tracking,
which represents not just the importance of parts of images but the trajectory
that users' gazes have over the whole duration of the video.

While saliency estimation and FoV tracking are not, in and of themselves,
optimizations that improve the QoE of 360° video streaming, they are closely
600 intertwined with all the other components that we discuss in this survey. The
most effective projection methods take user behavior into account [48], as pri-
oritizing the content that is watched most often will usually lead to a higher

compression efficiency. The same reasoning applies to QoE estimation: while we can look at the quality of a 360° frame from all possible angles, the actual
605 experience of users will always entail a single trajectory throughout the video, as their eyes can only look in one direction at a time. Naturally, different users might follow different paths during the videos, looking at different points at different times, and even the same user might focus on different content when rewatching an omnidirectional video, but this makes extensive studies of saliency
610 all the more important.

Finally, FoV tracking is a key component of streaming systems, as we will discuss in detail in Sec. 5: since QoE only depends on the parts of the video that the user is currently watching, buffer-aided streaming systems can improve their efficiency by predicting which direction the user will look and prefetching
615 the correct parts of the video, or adjusting the projection to improve quality in that direction. A precise, long-term FoV tracking can then enable the streaming client to make more foresighted choices,

4.1. Saliency evaluation

While there is a wide body of literature on 2D saliency evaluation [157],
620 omnidirectional video saliency is still a recent field. The Boolean Map Saliency (BMS) and Graph-Based Visual Saliency (GBVS) 2D saliency metrics were adapted to omnidirectional images and videos in [158], applying them directly on the omnidirectional images by using the ERP and automatically compensating for the distortion in the CIELAB color space [159]. Another attempt to adapt
625 saliency metrics to panoramic video was made in [160], using similar tools to compensate for the equirectangular distortion. A later work [161] considers multiple projections, taking into account the bias towards looking at the center of the panorama [162], i.e., keeping close to the equator of the video sphere [163], and combining it with 2D metrics. Other saliency metrics, taking center bias and
630 multi-object confusion into account, are proposed in [164] and [165]; the latter also includes a movement tracking framework. A metric considering a linear combination of low-level features and high-level ones such as faces and people

was proposed in [166], obtaining good results for images containing humans. It is also possible to apply 2D techniques such as weakly supervised CNNs directly
635 by using the appropriate projection and adjustments [167], or by using CNNs to correct the distortion, combining the output of the traditional saliency map of each path with its spherical coordinates [168]. Spherical CNNs can also be used directly [169].

In [170], a superpixel decomposition is applied to the image, which is then
640 converted to the CIELAB color space; the difference in contrast and color is then used to train an unsupervised learner to determine saliency, according to the boundary connectivity measure [171]. A similar approach is taken in [172], in which the authors derive sparse color features and apply a model of human perception, biased towards the equator, to derive saliency. It is also possible
645 to combine 2D saliency maps on different projections with spherical domain optimization to generate a hybrid metric [173], or to include illumination normalization [174] to compensate for lighting variations in the omnidirectional images. GANs [175] are another supervised learning tool that can be used to infer saliency; unsupervised learning from bottom-up features has also been applied
650 successfully [176]. An experimental comparison of several standard and omnidirectional state-of-the-art saliency detection techniques is presented in [177].

Scanpaths [178] are a natural extension of the saliency metric, adding the time dimension to the static map; image metrics can often be straightforwardly extended to the video domain, both for standard and omnidirectional
655 video [179]. Scanpaths can also act as predictors of future gaze directions when used as the training model for learning agents such as deep networks [180] or GANs [181]. However, scanpath models often have the same issues as static saliency models: since saliency is extremely content-dependent, different models can have higher performance on different datasets. For this reason, standard
660 evaluation datasets and metrics have been proposed [182, 183]. In [184], an approximate saliency metric is derived by clustering multiple users' head movements, but the training is video-specific and does not generalize on other content. A more general model based on user movement statistics is derived in [185] by

Table 6: Summary of the main presented saliency FoV prediction methods

Reference	Type	Basic principle
[181]	Content- and popularity-based	GAN
[184]	Popularity-based	Clustering
[187]	History-based	Dead reckoning
[188]	History-based	Polynomial regression
[189, 190]	History-based	Kalman filtering
[191, 192]	History- and popularity-based	Gaussian filtering
[193]	History- and popularity-based	Clustering
[194]	History- and popularity-based	CNN
[195]	History- and popularity-based	Recurrent Neural Network (RNN)
[195, 196, 197, 198]	Content-, history- and popularity-based	Long Short-Term Memory (LSTM)
[199]	Content-, history- and popularity-based	Convolutional LSTM
[200]	Content- and history-based	Attention-based encoder-decoder network

combining Fused Saliency Maps (FSMs) [186] with head movement data and
665 applying an equator bias.

In general, saliency evaluation is more related to coding and compression
than to streaming, as streaming systems have the benefit of knowing the current
trajectory of the user, which can lead to more effective FoV tracking tools
discussed below. On the other hand, the compression and coding phase must
670 be performed once, so saliency and most frequent scanpath estimation are the
only available tools to use content information during it. As with other fields,
the development of machine learning tools to combine content features and user
experience is one of the major research challenges: the field is rapidly developing,
and a one-step network that can automatically learn to extract saliency and
675 encode the video at the same time is just behind the corner.

A task related to saliency and scanpath estimation is automatic navigation,
i.e., moving through a panoramic video to catch the most important parts of the
action. A simple optimization is performed in [201], while another work [202]
proposes a combination of object recognition and reinforcement learning, im-
680 plementing the policy gradient technique to track interesting objects in sports
videos. A similar approach can be applied to explore a space by rewarding an
agent when it examines unexplored portions of its environment [203].

4.2. Field of View prediction

As discussed in Sec. 3, the viewport direction is a fundamental factor in
685 assessing the QoE of immersive video, and needs to be considered proactively
both in the coding phase and when performing adaptive streaming. In particu-
lar, the difficulty of predicting future viewport orientation leads to diminishing
returns on capacity, limiting the amount of prefetching [204] and exposing users
to the risk of annoying stalling events [115].

690 The prediction of gaze direction has been studied since the '90s by using
simple analytical tools, and it parallels the work on motion prediction: the first
studies used dead reckoning [187] and polynomial regression [188], and several
streaming systems that exploit FoV prediction still apply simple linear regres-
sion on historic data [205]. However, the models are often too simplistic, not
695 capturing viewer behavior complexity: an early frequency-domain analysis [206]
highlights the difficulty of predicting long-term trends using these strategies.
Kalman filtering approaches use similar underlying models, but they can deal
with imprecise measurements of the orientation [189, 190].

Recently, more complex statistical tools such as Gaussian filtering [191, 192]
700 and clustering [193] have been used with good results, modeling viewer gaze
direction as a random variable whose distribution is determined by their own
history as well as past users' behavior. Another study on the correlation in the
behavior of users [207] concentrates on the caching implications of predicting
FoV.

705 Recently, deep learning has also been applied to the problem, as FoV pre-
diction is a classical regression problem: both CNNs [194], and RNNs [195] had
good performance on standard datasets [208]. Three other works [196, 197, 198]
introduce LSTMs, including content-related metrics such as saliency maps and
scanpaths along with the motion information. In [209], ladder convolution is
710 used before the LSTM to extract contextual information from the encoded im-
age and correct for the projection. Naturally, a richer state with more infor-
mation from different sources can improve the quality of the prediction, which
is further enhanced in [200] by the use of an encoder-decoder network with an

attention mechanism that can have high tracking accuracy over multiple seconds. However, these methods have not been tested on large datasets yet, and their significant computational complexity poses a challenge in real-time mobile applications. The search for an efficient FoV tracking algorithm that can allow Dynamic Adaptive Streaming over HTTP (DASH) clients to achieve similar levels of buffer filling to traditional planar video is still open, and as these works are all from the past 3 years, the state of the field is rapidly changing and improving.

Prediction on even longer timescales is possible by leveraging the watching history of other users and identifying similarities [199], maintaining a viewport hit rate over 75% even at a distance of 10 seconds. For additional accuracy, users can be clustered by similarity [210, 211], identifying common patterns within clusters more effectively. This approach can also be combined with deep reinforcement learning [212] to reduce training costs. It is also possible to use combine saliency metrics and head movement with more precise gaze tracking, obtaining a higher precision in the prediction [213]. FoV prediction can also be tested on public datasets, often used by existing saliency estimation [177] and prediction methods [212]; the latter provides a dataset with the head movements of 58 users across 76 video sequences. The datasets used for QoE measurement often include both the ratings and head movements of the viewers, so they can also be used for this purpose. A dataset with the head movements of 59 users watching 7 YouTube immersive videos was presented in [214], while another dataset with partly overlapping videos and 50 different subjects was presented in [215]. Another dataset includes the head trajectories of 48 users watching 18 videos [216], and yet another [217] contains the FoV trajectories and saliency maps of 48 users on 24 videos. The dataset presented in [218] includes both head movements and the results of a cybersickness questionnaire for 20 subjects watching 48 video sequences. The same kinds of data are available in [219], with 60 subjects watching 28 videos, and in [220], with 20 subjects watching 5 videos created and edited by professional filmmakers. Another dataset [221] provides eye tracking data, which is more precise than head movements, for 98 static

Table 7: Available FoV tracking datasets

Reference	Type	Subjects	Videos
[212]	Head movements	58	76
[214]	Head movements	59	7
[215]	Head movements	50	10
[216]	Head movements	48	18
[217]	Head movements (with saliency maps)	48	24
[218]	Head movements (with cybersickness questionnaire)	20	48
[219]	Head movements (with cybersickness questionnaire)	60	28
[220]	Head movements (with cybersickness questionnaire)	20	5
[221]	Eye movements (static images)	63	98
[222]	Eye movements (desktop platform)	50	12

745 images, observed by 63 subjects for 25 seconds each. Viewer gaze direction is usually analyzed on VR headsets, but there is a public dataset [222] of immersive video FoVs on a desktop platform. The datasets on FoV prediction and tracking are summarized in Table 7, while the main methods of FoV prediction we presented in this section are summarized in Table 6.

750 5. Streaming

Serving omnidirectional video content over the Internet is a complex problem of its own: a naive approach sending the whole sphere at the highest quality will be extremely inefficient, and an intelligent way to adapt to network conditions and user behavior needs to be devised. In this section, we discuss the standardization work on omnidirectional video streaming and the solutions to 755 optimize bitrate adaptation by considering spatiotemporal elements such as FoV prediction. Finally, we present some of the work on network support of omnidirectional video in the context of VR, which is one of the key applications that will be enabled by 5G networks.

760 5.1. Streaming standardization

Today, the DASH streaming standard is almost universally used for 2D video streaming over the Internet: it divides videos into short segments, which are encoded independently and at several different qualities by the server. The streaming client can then choose the quality level for each segment, depending on the bitrate its connection can support, by requesting the appropriate 765

HTTP resource. The low computational load on the server and transparency to middleboxes make DASH highly compatible with the existing Internet infrastructure, and the possibility of implementing different adaptation algorithms makes it versatile to different network conditions. In the early 2010s, the standard was extended to enable the transmission of omnidirectional, zoomable and 3D content: the Spatial Representation Description (SRD) extension [223] specifies spatial information on each segment, allowing servers to present spatially diverse content. The standard only specifies the spatiotemporal coordinates of each segment, and the choice of which ones to download and show to the user is still client-side, in accordance with the client-based DASH paradigm.

The Omnidirectional Media Format (OMAF) standard [224] is another specification that can extend DASH or other streaming systems by specifying the spatial nature of video segments. Furthermore, OMAF also specifies some requirements for players, taking another step towards a complete standard specification for omnidirectional streaming. In fact, OMAF-based players have already been implemented and demonstrated [225]. The standard specifies a viewport-independent video profile using the HEVC coding standard, as well as two viewport-dependent profiles using HEVC or the older AVC, supporting the ERP and CMP projections and tile-based streaming. OMAF further defines a viewport-dependent projection approach, in which the client chooses the projection with the highest quality for its current viewport, as well as three different tile-based streaming approaches: in the simplest one, the viewport region is downloaded at a high quality, along with an additional low-quality version of the whole sphere. The other two allow a freer choice by the client, which can download a set of tiles with either mixed encoding quality or mixed resolutions, privileging the viewport area in both cases.

A DASH SRD or OMAF compliant server can allow clients to stream omnidirectional video, presenting either segments with different viewport-dependent projections or separate tiles for the client to choose. The client can download the appropriate projected content, potentially discarding or downloading low-quality versions of tiles with a low viewing probability and saving bandwidth.

It is also possible to exploit the features of HEVC to enable fast FoV switching or to give users the option to zoom into certain areas of the sphere [226], as high-quality chunks can be requested at any moment if the user moves
800 their head [227], seamlessly integrating the functions with minimal server-side changes. The techniques for streaming content at the highest possible quality exploiting viewport information are described in detail in the following.

5.2. Viewport-dependent streaming

Omnidirectional streaming has all the complexity of traditional streaming,
805 with buffer concerns and dynamic quality considerations, but it has an additional degree of freedom: since the viewer only sees the portion of the sphere in their FoV, quality is strongly dependent on the direction of their gaze [228]. The parts of the sphere inside the FoV are visualized by the user, and their attention focuses on a narrower foveal cone [229]. Naturally, adaptive streaming systems
810 try to exploit this by maximizing the quality of the predicted FoV at the expense of unwatched regions, which do not contribute to the QoE. This approach is not without pitfalls: standard DASH buffered streaming often prefetches segments several seconds in advance, with no performance loss, but prefetching an unwatched region at a high quality does not lead to any QoE improvement [230],
815 so the advantages of prefetching in adaptive 360° video are closely tied with the quality of the viewport prediction [204]. The paradigm can also deal reactively to dynamic viewpoint changes [231].

Transmission factors can significantly affect the quality of the image [115]: viewport-agnostic streaming, which transmits the whole omnidirectional video
820 with the same quality, does not introduce additional distortion, but it is extremely bandwidth-inefficient. There are two viewport-dependent approaches to adapting omnidirectional streaming systems to the FoV. The first, and most common, approach is tile-based streaming, which divides the omnidirectional video into independent rectangular tiles [232]. In this case, the bitrate adaptation becomes multi-dimensional [233]: each tile can be streamed independently
825 at a different quality level, and the client reconstructs the whole sequence. It

is also possible to exploit the HTTP/2 weight parameter to control the tile interleaving and prioritization [234]. The main downsides of tiling-based approaches are the frequent spatial quality fluctuations [235] and artifacts close to
830 tile borders.

The second approach is viewport-dependent projection, which uses offset projection [236] or differentiated QP assignment [237] to improve the quality of the FoV [238]. This approach avoids obvious seams between tiles at different qualities. However, it can have temporal quality fluctuations as the projection
835 changes when the user moves their head, and it is rarely used in the literature because of the server-side memory requirements of storing several different projections with different encoding parameters. A third, even less common, solution in wireless channels is to transmit the video directly, using analog modulation after applying the Discrete Cosine Transform (DCT) [239]. This leads to a more
840 graceful quality decrease than the sharp fall caused by digital transmission, but is not without its disadvantages, as the transmitter and receiver hardware need to be designed *ad hoc*.

In the following, we concentrate on tile-based streaming methods, as they are by far the most common, although they involve a higher computational
845 costs due to the necessity of stitching [183]. While the simplicity in the design of tile-based systems is attractive, we remark that they might not be optimal in terms of encoding efficiency, and a more holistic solution that takes both encoding efficiency and streaming factors into account might provide an even better solution in the future. As we discussed in the previous sections, the
850 design of projection and encoding methods is inextricably linked to the expected scanpath of the user's gaze, while the streaming adaptation strategy strongly relies on FoV prediction. As some users might behave in an atypical manner and follow uncommon scanpaths, the encoding system and streaming systems need to guarantee a minimum QoE in all cases, while optimizing the QoE for
855 as many users as possible. These conflicting objectives present an interesting trade-off, which is mostly unexplored in the current literature and would be extremely interesting to investigate.

An accurate prediction of the FoV can improve the efficiency of omnidirectional streaming significantly: since the only area that the viewer sees is the one in the viewport, other parts of the video sphere can be streamed with a much higher compression, or even discarded, without affecting the QoE. Several authors have proposed streaming algorithms exploiting this prediction, often using it in one of two ways:

- The *viewport-based* approach maximizes the quality of the predicted FoV, or a slightly wider region to account for inaccuracies in the prediction, and streaming the rest of the sphere at the lowest quality.
- The *probabilistic* approach weights the tiles by their viewing probability, then optimizing the expected quality.
- The *reinforcement learning* approach implicitly optimizes the expected long-term QoE by applying its namesake learning paradigm.

Naturally, the capacity of the connection is the constraint that limits the QoE, and various capacity prediction methods can be employed. Since there is no correlation between the capacity of the channel and the viewport orientation, the two predictions can be performed separately with different methods, and the use that the streaming adaptation algorithm makes of the results is usually not constrained by the prediction method. An interesting way to improve the prediction and the streaming quality is to devise the content in a way that implicitly or explicitly leads users to direct their attention in certain directions [240].

The viewport-based approach is simpler, as it does not require solving a complex optimization problem: there are only two regions, the one around the viewport and the rest of the sphere, and the second one is usually either not streamed at all or streamed at the maximum possible compression [241]. Naturally, the approach is optimal if the predictor is perfect. In [205], both a linear regression and a neural network-based prediction are tested with a simple algorithm that transmits a circular portion of the omnidirectional video, comprised of the circle inscribing the predicted viewport with an additional

safety margin. The authors assume that an efficient projection method is used and that capacity is constant. It is also possible to adapt the safety margin to the estimated prediction error variance [242], increasing the area in case of quick
890 head movements or highly unreliable predictions. Naturally, linear regression is not the only possible model: a second-degree model with constant acceleration is proposed in [243], and Support Vector Regression (SVR) with eye tracking data is used in [244]. The latter distinguishes a small attention area of about
895 10° close to the gaze direction, while the rest of the FoV is a larger sub-attention area. The two areas have different weights in the optimization, and a third area (non-attention) completes the sphere with the unwatched portions. This kind of three-tier optimization is a first step towards the probabilistic approach.

It is also possible to mix a popularity-based approach with linear regression: the scheme presented in [245] uses the two at the same time, weighting the
900 regression outputs by the popularity and fetching the predicted viewport tiles, with some margin for errors, at the highest quality supported by the connection. A more refined server-side approach is adopted in [246], which uses a neural network to estimate the future viewport of multiple users. The algorithm then sends the data for the predicted viewport to each user at the highest possible
905 quality, while sending the invisible parts of the sphere at the lowest one to save bandwidth. Another work [194] takes the same approach, replacing the fully connected neural network with a CNN. Object tracking is another kind of information that can be used for the prediction: this semantic information [247] is often correlated to users' viewing patterns, as their gaze follows one of the
910 object across the panoramic video.

The probabilistic streaming approach weights the quality of each tile by their viewing probability and optimize expected quality assuming constant capacity. This scheme has been combined with linear and ridge regression for the equirectangular [248], triangular [249], and truncated pyramid [250] tiling
915 schemes. In all three cases, the capacity of the connection is assumed to be constant. In [251], the linear regression is combined with a buffer-based streaming approach to maintain playback smoothness, adapting the estimate of the

total bitrate to control the buffer level. Bas-360 [252] is another scheme which combines spatial adaptation with a temporal factor, optimizing a sequence of
920 multiple future frames together and using stream prioritization and termination to correct bandwidth and FoV prediction errors. A similar method [253] considers both temporal and spatial quality smoothness in the optimization, considering a sequence of future segments. The Optimal Probabilistic Viewport (OPV) scheme [254] tackles prediction error from a different angle, correcting
925 its decisions by streaming higher-quality tiles for already buffered segments if necessary. This allows the client to keep a long buffer and avoid stalling without having to lower quality.

As for the viewport-based approach, popularity can be considered to perform the prediction: a proposed scheme [255] tries to maximize the overall
930 expected QoE, considering only the popularity of each tile, corrected for the equirectangular tiling (if the viewport is closer to the poles, more tiles will be part of the FoV). The algorithm considers the rate-distortion curve for each tile, weighted by its corrected navigation probability. In this case, capacity is assumed to be constant. This approach can also exploit the popularity of tiles
935 and linear regression jointly: in [256], a transition threshold between the two methods is set, and the popularity-based model is used if the measured capacity of the connection is insufficient to support the other one. The concept behind this scheme is that regression incurs a higher risk of rebuffering events in low-bandwidth scenarios, and switching to a more conservative scheme is desirable
940 in this context. Another work [257] mixing the two prediction methods uses a linear combination of the two outputs, considering the trade-off between the flexibility of the adaptation and the coding efficiency, which decreases as the number of tiles grows. A k-Nearest Neighbors (k-NN) was exploited in [258] to make use of previous users' data by finding similar scanpaths and assigning
945 future FoVs from those users a larger probability.

A more sophisticated approach, presented in [196], combines saliency and motion information with the FoV scanpath using an LSTM. The predicted viewing probability for each equirectangular tile can then be used in the usual

Table 8: Summary of the main presented FoV prediction-based streaming schemes

Ref.	Projection	Optimization	Prediction method
[205]	Ideal	Circular region around the viewport	Linear regression and neural networks
[242]	ERP	Adaptable region around the viewport	Linear regression
[243]	CMP	Highest quality for predicted viewport	Second-degree regression
[244]	ERP	Attention-based weights	SVR with eye tracking
[245]	ERP	Highest quality for predicted viewport	Popularity-weighted linear regression
[246]	ERP	Highest quality for predicted viewport	Neural network with motion history
[194]	ERP	Highest quality for predicted viewport	CNN with motion history
[247]	Direct	Highest quality for predicted viewport	Semantic object tracking
[248]	ERP	Expected quality	Linear regression
[249]	Triangular	Expected quality	Linear and ridge regression
[250]	TSP	Expected quality	Linear regression
[251]	ERP	Expected quality with buffer control	Linear regression
[252]	ERP	Expected quality over multiple future steps	Unspecified
[253]	ERP	Expected quality over multiple future steps	Unspecified
[254]	ERP	Expected quality, past action fixes	Unspecified
[255]	ERP	Expected quality	Popularity-based model
[256]	ERP	Expected quality	Popularity/linear regression switching
[257]	ERP	Expected quality	Popularity/linear regression linear combination
[258]	SP	Expected quality	k-NN with other users' patterns
[196]	ERP	Expected quality	LSTM with saliency, motion, and FoV info
[259]	ERP	Expected quality	3D-CNN with saliency, motion, and FoV info
[260]	ERP	Minimum visible quality, stalling avoidance	Unspecified
[261]	Unspecified	Reinforcement learning	Unspecified
[262]	ERP	Reinforcement learning	Neural network from [263]
[264]	ERP	Reinforcement learning	LSTM
[265]	ERP	Reinforcement learning	LSTM
[266]	ERP	Reinforcement learning	Implicit in the solution
[267, 268]	Adap. ERP	Expected quality	Known FoV
[263]	Adap. ERP	Expected quality	Popularity-based model
[269]	Adap.	Expected quality	Popularity-based model

probability-weighted quality optimization. The same technique was compared
950 to a 3D-CNN approach in [259]: both prediction methods had extremely good
performance, but the latter had a slight advantage.

A complete streaming algorithm, which considers stalling and a more so-
sophisticated capacity prediction method based on the harmonic mean of past
samples, is presented in [260]. The authors derive an efficient heuristic that can
955 maintain a high quality even when the FoV is uncertain, optimizing the quality
of the worst tile in the viewport to guarantee a minimum QoE while limiting

stalling. However, they do not present a specific FoV prediction method, but analyze performance as a function of the prediction error.

The third way to achieve the same objective without explicitly optimizing the expected QoE is to use Deep Reinforcement Learning (DRL): the sequential
960 approach reduces the multi-dimensional tile quality decision to a sequence of decisions for each single tile [261]. Another DRL solution [262] models the problem as a Markov Decision Problem (MDP), optimizing a complex function considering the FoV picture quality, quality variations, and stalling events. The
965 work assumes that FoV prediction is performed by a neural network, as in [246], and includes the prediction in the model state, along with the capacity and buffer history. Plato [264] is another system that assumes an external prediction as input to a DRL system, in this case performed by an LSTM. A similar solution was presented in [265], modeling buffer overflows explicitly. Another work using
970 DRL [266] performs the FoV prediction implicitly, using an LSTM to keep track of the historical trends in capacity and viewport orientation.

It is also possible to adaptively change the projection: in [267, 268], the compression or size of the tiles of an ERP can be changed according to the user's expected behavior and the expected quality resulting from each scheme. While
975 the authors assume that the future FoV is known in advance, which is obviously unrealistic, this kind of scheme adds a degree of freedom to the streaming optimization. It is also possible to use the adaptive projection with popularity-based prediction, as in [263]. In [269], the popularity-based prediction is used to derive an adaptive projection with an irregular shape. The trade-off between
980 changing the compression of the tiles at the same resolution and lowering the resolution to increase the bandwidth efficiency has also been explored [100], and the results show that the viewport-based approach has a higher QoE with the same compression.

Techniques based on packet-level coding or Scalable Video Coding (SVC) [270,
985 271] are also possible: a scheme that protects immersive video data with fountain codes, increasing the redundancy for areas in the FoV while leaving unwatched areas of the sphere unprotected, has been proposed in [272]. In a multipath

wireless scenario in which multiple links with fast-varying capacity are available, it is possible to use a wireless path to transmit the video’s base layer and
990 another to to transmit enhancement layers, improving the quality of live VR streaming while maintaining full reliability [273].

5.3. Network-level innovations

The DASH paradigm is entirely end-to-end, and does not require any network support. However, several studies have explored the possibility of implementing explicit network support for video streaming: the network can either
995 explicitly communicate with the client and help it make decisions, or provision resources and indirectly improve the situation perceived by the client, which will then improve the video quality autonomously. Since immersive streaming requires more resources from the network, implicit or explicit support is even
1000 more helpful in this scenario.

The most basic form of network support for immersive video is at the design level: the lower layer protocols and their interplay can negatively affect the 360° stream, and design adjustments based on an analysis of these effects can significantly improve performance. Such a study was performed for the LTE
1005 network [274], finding several simple solutions that can be implemented without changing the network architecture. The standardization of the 5G requirements and solutions for immersive and VR video streaming are ongoing [275].

Caching is another form of basic network support that can be implemented simply, and is often already in place thanks to Content Delivery Networks
1010 (CDNs). Explicitly considering the nature of immersive video can significantly enhance the efficiency of edge caching strategies [276, 277]: by caching the most common fields of view closest to the network edge [278], it is possible to increase the cache hit rate and, consequently, the average QoE. Caching can be combined with edge computing strategies to improve the QoE of Augmented
1015 Reality (AR) [279], rendering the virtual content in the user’s FoV without the latency that cloud processing entails. It is also possible to extend these techniques, along with a measure of user popularity at any given moment, to

optimize multicast immersive streaming in mobile networks [280].

More explicit approaches aim at resource allocation when multiple Radio Access Technologies (RATs) are available [281], exploiting FoV prediction to pair
1020 users with access points and effectively use wireless resources. The same optimization can be performed for multiple users on the same network, maximizing the overall QoE by cooperatively downloading different SVC layers [282]. FoV prediction can also be used in multicast scenarios, clustering users with similar
1025 points of view and exploiting mmWave multicast [283] to serve them together. With the gradual adoption of 5G technology, it is also possible to combine cellular resource scheduling optimization with encoding tile rate selection [284] to provide low delay upload of VR content.

Live streaming of AR and VR content is another issue, which is complicated
1030 by the limited delay tolerance: experimental studies [285, 286] show that any delay over 10 ms can be perceived by users as annoying, although higher latencies can be tolerated [287]. The issue becomes even more complex when viewport-adaptive schemes are taken into account, as the adaptation scheme needs to react fast enough to changes in the FoV to avoid quality drops [237]. Future
1035 networks need to be able to guarantee reliable end-to-end communication below this latency, requiring innovation both from the physical [288] to the transport layer [289] to enable these applications.

However, network support is not limited to communication: in the case of rendered VR, the network can also help with computation tasks. Most VR
1040 platforms are tethered, using a desktop computer to render the environment in real-time: current smartphones do not have the computing and battery power to provide a high-quality VR experience without offloading some of the computational load [290]. Several works have tried to mitigate the latency problems caused by the remote rendering, either by reducing the throughput using compression [291] or by using servers close to the network edge [292]. The Furion
1045 platform [293] tries to solve this issue by using FoV prediction techniques to prefetch rendered background content from a remote server, rendering only the foreground objects locally. The use of Mobile Edge Computing (MEC) to pro-

vide rendering support to multiple VR users at the same time has also been
1050 investigated [294]. The several components of latency in a VR application were
analyzed in [295]: the trade-off between network and computation delay, as
cloud servers are more powerful but farther away, is a critical design choice for
future systems.

6. Conclusions and open challenges

1055 Omnidirectional video has gained significant traction, both in the research
community and in the industry, and the first commercial HMDs are now several
years old. This kind of video presents challenges that call for a redesign of the
whole video coding, streaming and evaluation pipeline, taking into account two
critical aspects specific to 360° video: geometric distortion due to the mapping
1060 of a spherical surface to 2D planes, and the fact that viewers only experience a
limited FoV.

In this survey, we analyzed all aspects of omnidirectional video coding and
streaming. First, we reviewed projection methods and the geometric distortion
that they can cause, with a description of their effects on video encoders and
1065 their compression efficiency. The choice of a projection scheme is often a trade-
off between different types of distortion: while approaches based on solids with
a larger number of faces approximate the spherical nature of the image better,
they also increase the number of edge distortion, and thus the possibility of
visible errors at the seams. The same is true for offset projection: dedicating
1070 more pixels to the most probable view increases the average QoE, but highly
reduces it if the user turns around unexpectedly. The subsequent encoding
parameters also have effects on the image quality, and they should be optimized
jointly with the projection settings.

The projection and encoding of omnidirectional videos is a critical procedure,
1075 as it determines the rate-distortion efficiency of the video streaming system. The
research on the subject has evolved far from the first simple examples using
simple projection schemes and the 2D encoding pipeline, but some fundamental

trade-offs limit possible performance. In particular, the choice of projection affects the rest of the encoding pipeline significantly, and *ad hoc* region-adaptive
1080 quantization schemes need to be devised. Motion models and inter-frame compression also need to be carefully tuned, as no projection can avoid geometric distortion and discontinuities caused by objects crossing face boundaries at the same time.

We then focused on QoE in omnidirectional video: as several subjective
1085 studies prove, 2D quality metrics are inaccurate in this scenario, and more intelligent ones that take geometric distortion and viewer attention are needed. The dynamic factor also plays a role, as quality variations between segments and tiles can affect QoE in unpredictable ways. In general, measuring QoE in omnidirectional video is a complex problem, and will probably require the use of
1090 content-aware learning tools. We then discussed automatic saliency estimation and FoV prediction techniques, which have a critical role in QoE estimation and video streaming: being able to predict the FoV, both for the average user and for the current viewing session, can help compress video better by allocating more pixels to regions with more important content and which are viewed more often,
1095 but also increase the efficiency of tile-dependent streaming and the accuracy of QoE metrics.

The strong dependence between video content and the effectiveness of different metrics, along with the lack of a single large-scale database of experimental results to use, can result in contradictory evidence, and multiple studies often
1100 have different outcomes. However, there are a few guidelines for future research: the inadequacy of 2D metrics such as PSNR in the omnidirectional video domain is evident from most studies, even when corrected and weighted to account for the different geometry. VIFP seems to be a promising base to develop better omnidirectional QoE metrics, but the hot topic in the field is machine learning: a few learning-based metrics have already been proposed, but they have
1105 not been tested on a wider scale or released publicly. Whether the significant performance improvements that machine learning achieved in other applications can be replicated in QoE measurement of omnidirectional video is arguably the

biggest open question. Another important, and often overlooked, factor is the
1110 dynamic nature of video, which can be crucial in omnidirectional video due to
the cybersickness issue: the study of dynamic metrics for omnidirectional video
taking stalling events and quality fluctuations due to the adaptive streaming
and the user’s head movements into account is still limited to a few works.

Streaming itself is another active research topic: we considered the three
1115 most common approaches to tile-based streaming as well as a brief overview of
viewport-dependent streaming. In particular, schemes that weigh the tiles by
their viewing probability and importance in the projected FoV and maximize the
overall expected QoE, often including dynamic factors such as stalling and qual-
ity variations in the optimization, obtain the best performance. However, better
1120 FoV prediction is not the only way to improve streaming systems: additional
options such as adaptive tiling schemes and SVC are also being investigated,
as they can increase bandwidth efficiency and robustness in mobile streaming
scenarios. Reinforcement learning-based schemes have recently been under their
spotlight, as they can seamlessly integrate data from different sources in their
1125 prediction and optimize even complex QoE functions in difficult scenarios with
little design effort. Learning-based solutions provide higher accuracy and al-
low prediction for up to 10 seconds, a critical requirement to avoid stalling in
buffer-based streaming systems.

Finally, network-level optimization to support omnidirectional streaming
1130 and VR is another subject that is beginning to attract interest: the promises
of 5G with regard to resource allocation and optimization, higher capacity, and
edge and fog computing provide new interesting scenarios to simplify streaming
systems and enable VR over simple devices with limited battery and computing
power.

1135 Streaming techniques, along with all other aspects of omnidirectional video
coding and evaluation, are rapidly converging towards machine learning as a
general solution: the complexity of omnidirectional videos requires a level of
context-awareness that is too complex for traditional analytical techniques. Fur-
thermore, the trend in the field is towards *joint* optimization, not considering

1140 each step of the process separately but optimizing them all at once, from projec-
tion and coding to streaming and quality evaluation. The first fully integrated
models, incorporating historical data from other users, spatial and temporal
features of the content, and past history for the specific user, are beginning to
appear in the literature, although larger datasets with a varied population of
1145 viewers for proper evaluation are not available yet. Gaze tracking, which is more
precise than head orientation tracking, is another possibility that is still largely
unexplored due to the cost and complexity of the required experimental setup.
However, the research related to several of the topics presented in this survey
is still ongoing, and, given the fast update rate of communication technologies
1150 and the rapid growth of deep learning, we can expect the interest in the topic
not to fade. In particular, VR is central to the 5G paradigm, and innovations
in each of the subjects we considered is needed to meet the high expectations.

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2135 Glossary

- ACR** Absolute Category Rating.
- AR** Augmented Reality.
- AV1** AOMedia Video 1.
- AVC** Advanced Video Coding.
- 2140 **BMS** Boolean Map Saliency.
- BP** Back Propagation.
- CDN** Content Delivery Network.

CMP Cubic Mapping Projection.

CNN Convolutional Neural Network.

2145 **CP-PSNR** Content Preference PSNR.

CP-SSIM Content Preference SSIM.

CPP-PSNR PSNR for Craster Parabolic Projection.

DASH Dynamic Adaptive Streaming over HTTP.

DCR Degradation Category Rating.

2150 **DCT** Discrete Cosine Transform.

DeepVR-IQA Deep VR Image Quality Assessment.

DMOS Differential Mean Opinion Score.

DRL Deep Reinforcement Learning.

DSIS Double Stimulus Impairment Scale.

2155 **ERP** Equirectangular Projection.

FoV Field of View.

FSIM Feature Similarity Index.

FSM Fused Saliency Map.

GAN Generative Adversarial Network.

2160 **GBVS** Graph-Based Visual Saliency.

GoP Group of Picture.

HEVC High Efficiency Video Coding.

HMD Head-Mounted Display.

ITU International Telecommunication Union.

²¹⁶⁵ **JVET** Joint Video Exploration Team.

k-NN k-Nearest Neighbors.

LSTM Long Short-Term Memory.

MC360IQA Multi Channel 360° Image Quality Assessment.

MDP Markov Decision Problem.

²¹⁷⁰ **MEC** Mobile Edge Computing.

MOS Mean Opinion Score.

MS-SSIM Multiscale SSIM.

MSE Mean Square Error.

NIQE Natural Image Quality Evaluator.

²¹⁷⁵ **NPCM** Nested Polygonal Chain Mapping.

NQQ Normalized Quality versus Quality factor.

OCP Offset Cubic Projection.

OMAF Omnidirectional Media Format.

OPV Optimal Probabilistic Viewport.

²¹⁸⁰ **PSNR** Peak Signal to Noise Ratio.

PVQ Perceptual Video Quality.

QAVR Quality Assessment in VR systems.

QoE Quality of Experience.

- QP** Quantization Parameter.
- 2185 **RAT** Radio Access Technology.
- RBM** Rhombic Mapping.
- RNN** Recurrent Neural Network.
- RSP** Rotated Sphere Projection.
- S-PSNR** Sphere-based PSNR.
- 2190 **S-SSIM** Spherical SSIM.
- SAO** Sample Adaptive Offset.
- SCP** Shared Coded Picture.
- SISBLIM** Six-Step Blind Metric.
- SP** Sinusoidal Projection.
- 2195 **SRD** Spatial Representation Description.
- SSIM** Structural Similarity Index.
- SVC** Scalable Video Coding.
- SVR** Support Vector Regression.
- TSP** Truncated Square Pyramid.
- 2200 **V-CNN** Viewport-based CNN.
- VIFP** Visual Information Fidelity in Pixel Domain.
- VR** Virtual Reality.
- VVC** Versatile Video Coding.
- WS-PSNR** Weighted to Spherically Uniform PSNR.
- 2205 **WS-SSIM** Weighted to Spherically Uniform SSIM.