

# UAV Immersive Video Streaming: A Comprehensive Survey, Benchmarking, and Open Challenges

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**Abstract**—Over the past decade, the utilization of unmanned aerial vehicles (UAVs) has witnessed significant growth, owing to their agility, rapid deployment, and maneuverability. Among various applications, capturing videos using UAVs has emerged as a prominent and promising use case, enabling diverse applications such as remote surveillance and gaming. In particular, the use of UAV-mounted 360-degree cameras to capture omnidirectional videos has enabled truly immersive viewing experiences with up to six degrees of freedom (6DoF). However, achieving this immersive experience necessitates encoding omnidirectional videos in high resolution, leading to increased bitrates. Consequently, new challenges arise in terms of latency, throughput, perceived quality, and energy consumption for real-time streaming of such content. This paper presents a comprehensive survey of research efforts in UAV-based immersive video streaming, benchmarks popular video encoding schemes, and identifies open research challenges. Initially, we review the literature on 360-degree video coding, packaging, and streaming, with a particular focus on standardization efforts to ensure interoperability of immersive video streaming devices and services. Subsequently, we provide a comprehensive review of research efforts focused on optimizing video streaming for time-varying UAV wireless channels. Additionally, we introduce a high-resolution 360-degree video dataset captured from UAVs under different flying conditions. This dataset facilitates the evaluation of complexity and coding efficiency of software and hardware video encoders based on popular video coding standards and formats, including AVC/H.264, HEVC/H.265, VVC/H.266, VP9, and AV1. Our results demonstrate that HEVC achieves the best trade-off between coding efficiency and complexity through its hardware implementation, while AV1 format excels in coding efficiency through its software implementation, specifically using the libsvt-av1 encoder. Furthermore, we present a real testbed showcasing 360-degree video streaming over a UAV, enabling remote control of the drone via a 5G cellular network. Finally, we discuss open challenges and outline future research directions for efficient and low-latency immersive video streaming using UAV.

**Index Terms**—UAV, 360°, low latency, video coding.

## I. INTRODUCTION

**I**MMERSIVE video technology enables users to experience a quasi-realistic virtual environment, fostering engagement and a sense of presence in a digital space. Various visual media modalities, such as volumetric, light field, and omnidirectional video (ODV), have emerged as viable options for delivering an immersive viewing experience [1]. Among these, ODV,

commonly known as 360-degree video, has gained widespread popularity due to the availability of acquisition and display devices, as well as standardization efforts ensuring interoperability. Integrating real-time transmission of 360-degree video using a UAV-mounted camera enhances the immersive viewing experience by adding an extra degree of freedom through UAV mobility. This advancement holds promise for diverse applications like remote video surveillance, scientific exploration, autonomous manufacturing assistance, agricultural monitoring, and more. However, this acquisition system for 360-degree video presents new challenges in delivering high quality of experience (QoE), primarily due to the limited computational and energy resources of UAVs and the rapid fluctuations of wireless channels. Additionally, the need for high-quality video and ultra-low end-to-end (E2E) latency becomes crucial to ensure real-time control of the UAV, especially in dynamic mobility conditions, further amplifying these challenges.

Addressing the above challenges will require efforts to enhance the communication for UAVs and develop adaptive and low-complexity schemes for 360° video encoding and streaming. In Table I, we present a summary of recent efforts [2]–[18] surveying the state-of-the-art research on communication for UAVs and immersive streaming. The literature in Table I can be broadly classified into two categories: covering the communication aspects of UAVs or the streaming of 360° videos. The authors in [2]–[4] presented a comprehensive survey of challenges and fundamental tradeoffs in designing wireless networks involving the UAVs. In particular, Mozaffari *et al.* [2] described various analytical frameworks and tools to address the design challenges, and Hayat *et al.* [4] surveyed the quality of service, connectivity, safety, and other general networking requirements for unmanned aircraft systems in civilian applications. Similarly, Baltaci *et al.* [5] reviewed the connectivity requirements for aerial vehicles, especially for piloting applications, and advocated achieving these stringent connectivity requirements through multi-technology heterogeneous networks. In [3], [6], the authors evaluated various enabling 6G technologies highlighting their benefits and drawbacks regarding their integration in a 6G wireless network with UAVs. They also discussed the design issues associated with integrating the UAVs into the wireless networks in the presence of these technologies. Further, authors in [7] surveyed the channel models for air-to-ground and air-to-air channel models for UAV communication.

To meet high data rate requirements for UAVs, Xiao *et al.* [8] reviewed relevant antenna structures and channel models for mmWave. Furthermore, the technologies and solutions

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TABLE I  
SUMMARY OF THE STATE OF THE ART

Category	Summary	References
Communication for UAVs	Covered topics	
	<ul style="list-style-type: none"> <li>Fundamental design tradeoffs</li> <li>Connectivity requirements</li> </ul>	[2], [4], [5]
	Enabling technologies for UAV's integration into 6G networks: <ul style="list-style-type: none"> <li>Intelligent reflecting surfaces</li> <li>millimeter wave (mmWave) connectivity</li> <li>Short-packet communication</li> <li>Integrated communication and sensing</li> </ul>	[3], [16]
	Wireless channel model for UAV-to-ground channel and vice versa	[7]
	mmWave-enabled UAV wireless networks	[8]
	Joint communication, control, and computation design	[9], [10], [14]
	Standardization, experimentation, and prototyping	[11]–[13]
	Interference issues in UAV networks	[9], [11]
360° video streaming	Various aspects of 360° streaming: <ul style="list-style-type: none"> <li>360° video delivery architecture</li> <li>Viewport dependent, viewport independent, and tile based solutions</li> </ul>	[15], [18]
	Issues pertaining to networks for 360° streaming	[15], [16]
	Compression and coding for 360° streaming	[16]
	Video streaming (two-dimensional (2D)) from aerial platforms	[17]

for UAV-connected mmWave cellular networks and mmWave-UAV ad hoc networks were discussed. The authors in [9] and [10] reviewed the methods for communication and trajectory co-design. In addition, Zeng *et al.* [9] surveyed various techniques to deal with the air-to-ground interference issues in cellular communication with UAVs. Fotouhi *et al.* [11] investigated the interference issues and potential solutions addressed by standardization bodies for serving aerial users with the existing terrestrial base stations (BSs). In addition, they reviewed the ongoing prototyping, testbed activities, and regulatory efforts to manage the commercial use of UAVs, along with cyber-physical security of UAV-assisted cellular communication. In [12], Marojevic *et al.* presented the architecture of aerial experimentation and research platform for advanced wireless, which facilitates experimental research in controlled yet production-like environments. In [13], Abdalla *et al.* surveyed the ongoing Third Generation Partnership Project (3GPP) standardization activities for enabling networked UAVs, requirements, envisaged architecture, and services provided by UAVs. The authors in [14] studied the UAV networks from the perspective of cyber-physical systems and considered the joint design of communication, computation, and control to improve the performance of UAV networks.

On the other hand, the work in [15]–[17] surveyed the adaptive streaming techniques for 360° videos. Yaqoob *et al.* in [15] reviewed the adaptive 360° video approaches that dynamically adjust the size and quality of the viewport. In addition, they surveyed the standardization efforts for 360° video streaming, highlighting the main research challenges such as viewport prediction, QoE assessment, and low latency streaming for both the on-demand and live 360° video streaming. Further, [16] surveyed the field-of-view (FoV) prediction methods, compression, and coding schemes for reducing the bandwidth required for streaming immersive videos. In addition, they reviewed caching strategies and datasets for

immersive video streaming. The work in [17] focused on the issues pertaining to 2D video streaming from an aerial platform. In particular, they surveyed the works using artificial intelligence (AI)-based techniques for enhancing video transmission performance.

We emphasize that none of the above papers have explicitly surveyed the issues relevant to immersive video streaming from a UAV platform, which poses unique challenges regarding computational complexity, quality, and E2E latency. In this work, we present a survey of solutions related to state-of-the-art schemes for immersive video streaming from a UAV and benchmark the existing video encoding schemes. In this direction, our contributions are the following:

- Review exiting wireless communication techniques for video streaming using UAV.
- Build a new dataset of immersive 360° videos captured from UAV in different acquisition conditions and scenes.
- Assess the coding efficiency and complexity of software and hardware encoders of five video standards and formats for immersive 360° video streaming.
- Discuss open challenges related to ODV streaming over UAV.

The rest of this paper is organized as follows. Section II presents the main components of the ODV streaming chain, including acquisition, encoding, packaging, rendering, and optimization. Then, the key performance metrics and wireless optimization techniques for UAV 360° video streaming are presented in Sections III and IV, respectively. In Section V, first the proposed UAV 360° video dataset is presented, and then benchmark and analysis of software and hardware encoders of five video standards are provided in Section VI. Next, the challenges of ODV streaming over UAV are discussed in Section VII. Finally, Section VIII concludes the paper.

## II. OMNIDIRECTIONAL VIDEO STREAMING

Figure 1 illustrates the E2E ODV streaming pipeline. In this section, we briefly review the technology used at the different stages to deliver ODV to the end user over the network.

### A. Acquisition and Preprocessing

An omnidirectional visual signal is presented in a spherical space with angular coordinates: the azimuth angle  $\phi \in [\pi, -\pi]$ , and the elevation or polar angle  $\theta \in [-\frac{\pi}{2}, \frac{\pi}{2}]$ , assuming a unit sphere (radius  $r = 1$ ) for acquisition and rendering. The sphere's origin represents the viewing reference that captures the light coming from all directions. In practical applications, an omnidirectional visual signal is captured using a multi-view wide-angle acquisition system, often utilizing fish-eye lenses. While a single eye-fish camera can only capture a partial sphere, combining multiple acquisitions from such cameras allows for complete sphere coverage through the process of *stitching* the images together [19]. However, the *stitching* operation introduces two main challenges. The first challenge involves blending and wrapping non-overlapping captured images, while also addressing inconsistencies in illumination and color that may arise after stitching. The

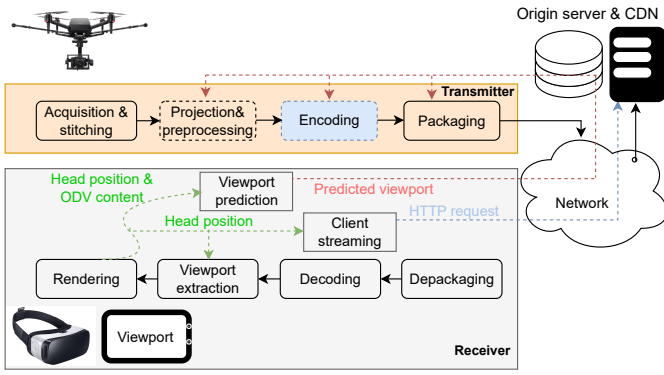


Fig. 1. ODV E2E streaming pipeline.

second challenge arises when dealing with video signals, as the camera sensors need to be perfectly synchronized. To facilitate further processing, the omnidirectional visual signal in spherical representation is then mapped to a 2D texture signal during the pre-processing stage, prior to encoding using conventional 2D video coding standards. The most commonly used mapping technique is known as equirectangular projection (ERP), which is particularly well-suited for production and contribution purposes. However, more advanced mapping techniques, such as equi-angular cubemap (EAC), cube map projection (CMP), and truncated square pyramid (TSP), have been proposed in the literature [20]. Notably, CMP and TSP offer enhanced coding efficiency, achieving bitrate savings of 25% and 80%, respectively, compared to ERP, making them more suitable for distribution purposes [21].

## B. Encoding

After mapping the sphere in a 2D plane, ODV content is encoded in practice by conventional 2D video standards such as advanced video coding (AVC)/H.264 [22], high-efficiency video coding (HEVC)/H.265 [23] versatile video coding (VVC)/H.266 [24], as well as VP9 and AOMedia video 1 (AV1) video formats. In particular, tailored coding tools are integrated into the HEVC/H.265, VVC/H.266 standards to enhance the ODV coding efficiency and enable advanced streaming features, improving the user's QoE. Yet, some non-normative coding techniques were proposed in the literature, encoding the ODV content in spherical representation to prevent projection distortions, resulting in higher coding efficiency.

1) *HEVC/H.265 Tools for ODV:* The tile concept in HEVC/H.265 plays a crucial role in enabling independent and parallel encoding/decoding of rectangular regions within the picture. By breaking the dependency of context prediction in arithmetic encoding and intra prediction, tiles allow for efficient processing and coding of specific regions [25]. Additionally, the tile boundaries also enable the possibility of disabling in-loop filters, further enhancing the flexibility of the encoding process. Moreover, the introduction of the motion-constrained tile set (MCTS) technique in HEVC/H.265, along with supplemental enhancement information (SEI) messages, extends the tile concept to the sequence of frames. This

technique restricts the MV to a selected set of tiles in the reference picture, thereby enabling the download and decoding of only the tiles within the displayed viewport during ODV streaming. This approach significantly improves the user's QoE by delivering high-quality content while efficiently utilizing bandwidth. However, the limitation of restricting motion vectors (MVs) within a set of tiles in the reference picture can have a negative impact on coding efficiency. To overcome this, the literature proposes non-normative solutions that enhance inter-prediction by utilizing the base layer as a reference in the scalable HEVC extension [26]. Alternatively, Bidgoli *et al.* [27] propose an enhanced intra-prediction technique with fine granularity random access capability, allowing end-users to request specific parts of the stream while ensuring efficient intra-coding. Furthermore, in the context of spherical bitrate allocation, a new entropy equilibrium optimization (EEO) strategy is proposed in [28]. This strategy derives the Lagrangian multiplier at the block level, which is used in rate-distortion optimization. The proposed solution, evaluated with ERP and CMP projection methods, demonstrates significant bitrate gains when compared to the HEVC reference software encoder [28].

2) *VVC/H.266 Tools for ODV:* The VVC/H.266 standard introduces several advancements for efficient encoding of ODV content, including the ability to signal the used projection technique and the definition of tailored coding tools [24]. In the case of 360-degree representation and ERP mapping, objects can span across the left and right picture boundaries continuously. Consequently, in VVC/H.266, inter-prediction samples may wrap around from the opposite left or right boundary when MVs point outside the coded area. Additionally, virtual boundaries are defined to skip in-loop filters across edges. For CMP projection, where cube maps may exhibit content discontinuities, virtual boundaries can be signaled to disable in-loop filtering and prevent artifacts arising from non-homogeneous boundaries. Furthermore, VVC/H.266 introduces the concept of subpictures, which allows for the extraction of independent rectangular regions within the picture, specifically designed for viewport-dependent VVC streaming applications. Subpictures offer two critical improvements over the previous MCTS concept. Firstly, subpictures enable MVs to refer to blocks outside the subpicture, and padding at subpicture boundaries is permitted, similar to picture boundaries. This new feature demonstrates higher coding efficiency compared to the tight motion constraints applied in MCTS. Secondly, the need to rewrite slice headers when extracting a sequence of subpictures to build a new VVC/H.266 compliant bitstream is eliminated, streamlining the encoding process [24].

3) *Learning-Based Coding for ODV:* Machine learning techniques have been extensively investigated in the literature to optimize and improve the coding efficiency of ODV content. In [29] a convolution neural network (CNN) was trained to learn the rotation of the sphere, resulting in the highest coding efficiency. This rotation is applied as a pre-processing step along the spherical axis before projection, leading to different rotations of the cube map. Experimental results demonstrated that incorporating rotation prediction achieved a significant coding gain of 8% to 10% with a prediction accuracy of 80%.

Similar to conventional video standards, learning-based video codecs can encode ODV content after its projection onto a 2D plane. Initially, the 2D representation is transformed into a compact latent space using an analysis transform based on an artificial neural network (ANN). The resulting latent representation is then encoded with a lossless entropy encoder to construct the bitstream. At the decoder side, a synthesis transform, also based on an ANN, reconstructs a version of the input 2D representation from the received bitstream. Moreover, the hyperparameters of the latent space entropy distribution, such as mean and variance, are encoded using an auto-encoder and utilized by the encoder and decoder to enhance the performance of the entropy encoder [30].

### C. Transport Protocols

Various packaging protocols can be employed for streaming ODV content, allowing the selection of a suitable protocol based on the specific application and end-user requirements concerning video quality, latency, and advanced functionalities provided by the protocol [31]. In the following, we outline the key characteristics of two widely utilized streaming protocols: omnidirectional media format (OMAF) and web real-time communication (WebRTC). Specifically, we provide an overview of the primary features of these protocols for ODV streaming. For a more comprehensive understanding, readers are encouraged to consult the comprehensive overview papers on OMAF [32] and WebRTC [33].

1) *OMAF*: The ISO/IEC 23090-2 standard, also known as OMAF, is a system standard developed by motion picture experts group (MPEG) with the objective of ensuring device and service interoperability for storing and streaming omnidirectional media content. This includes various forms of media such as 360° images and videos, spatial audio, and associated text. The initial version of the standard, completed in October 2017, provides fundamental tools for streaming 360° images and videos, enabling a three degrees of freedom (3DoF) viewing experience. In the subsequent release of the standard in October 2020, the second version introduced additional tools to support more advanced features. These features include enhanced viewport-dependent streaming, overlay capabilities, and the ability to stream multiple viewpoints, marking the initial steps towards achieving a 6DoF viewing experience. The specifications of OMAF are organized into three main modules: content authoring, delivery, and player. Furthermore, these specifications serve as extensions to the ISO base media file format (ISO/BMFF) and dynamic adaptive streaming over HTTP (DASH), ensuring backward compatibility with conventional 2D media formats. OMAF supports three types of omnidirectional visual signal representations: projected, mesh, and fish-eye. Each of these formats requires specific pre-processing for encoding and post-processing for rendering and display. Among the projected formats, OMAF includes support for two widely used projection algorithms: ERP and CMP. Additionally, OMAF incorporates a region-wise packing (RWP) operation, which allows for optional pre-processing operations prior to encoding. These operations include resizing, repositioning, rotation by 90°, 180°, and 270°, as well

as vertical and horizontal mirroring of specific rectangular regions. RWP serves various purposes, such as signaling the exact coverage of a partial spherical representation, generating viewport-specific (VS) video, enhancing coding efficiency, or compensating for over-sampling in the pole areas of ERP. The RWP metadata indicates the applied operations to the player, which then performs inverse operations to map the regions of the decoded picture back into the projected picture. This ensures proper rendering and display of the content, aligning with the intended transformations specified by the RWP.

In addition, the OMAF standard offers tools for viewport-dependent ODV streaming, which enables the selection of segments covering the user's viewport at high quality and other segments at lower quality and bitrate. This approach allows for more efficient utilization of network bandwidth, resulting in an improved user experience. Viewport-dependent ODV streaming can be achieved through two methods: viewport-specific and tile-based streaming. In the viewport-specific approach, multiple VSs are created and signaled, each encoding different viewports at high quality. Users can select the appropriate VS stream based on their viewing orientation. The OMAF region-wise quality ranking (RWQR) metadata can be used to signal the quality of different regions in the sphere. In the tile-based configuration, the ODV is divided into independent rectangular regions called *tiles*. Each tile only depends on the co-located tile in the sequence and can be decoded independently from other tiles. There are two alternatives for encoding video in independent regions. The first method utilizes the HEVC tile concept, where tiles are grouped into motion-constrained slices known as motion-constrained tile set. The second method, applicable to AVC which does not support tiles, partitions the video into sub-picture sequences, each representing a spatial subset of the original sequence. These sub-picture sequences are then encoded with motion constraints and merged into tiles in a single bitstream. Each tile or sub-picture sequence is stored in its respective track. Additionally, tiles can be encoded in different bitrates and resolutions, allowing users to select the optimal combination of tiles based on their viewing orientation, available bandwidth, and decoding capability.

The OMAF standard specifies six video media profiles that define the type of video representation and the supported video standard with its associated levels. For example, the "HEVC-based viewport-independent" profile uses the ERP projected representation and is constrained to HEVC Main 10 profile level 5.1. This level limits the spatial resolution to 4K (4096 × 2048). However, the "unconstrained HEVC-based viewport-independent" profile, introduced in the second edition, supports all HEVC Main 10 profile levels, thus increasing the decoding capacity and display resolution. Furthermore, there are already several open-source implementations available that support the first<sup>1</sup> edition of the OMAF standard. Further, some tools of the OMAF second edition have been demonstrated in [34], [35].

2) *WebRTC*: The WebRTC framework is an open-source solution specifically designed to facilitate real-time and low-

<sup>1</sup>NOKIA: <https://github.com/nokiatech/omaf>, Fraunhofer HHI: <https://github.com/fraunhoferhhi/omaf.js>, Intel Open Visual Cloud: <https://github.com/OpenVisualCloud/Immersive-Video-Sample>.

latency video transmission. Within the WebRTC transmitter, the "video collector" module takes on the responsibility of video encoding and encapsulating the encoded video frames into real-time transport protocol (RTP) packets. These packets are subsequently transmitted using the secure real-time transport protocol (SRTP) protocol. On the receiver side, relevant information regarding the received RTP packets is collected, and this information is relayed back to the "video collector" through the transport-wide feedback message of the real-time transport control protocol (RTCP) protocol. The "bandwidth controller" module, located within the "video collector," utilizes these control messages to compute essential network metrics such as inter-packet delay variation, queuing delay, and packet loss. These metrics play a crucial role in determining the target bitrate, which is then employed by the rate control module of the video encoder. The rate control module dynamically adjusts the encoding parameters, such as the quantization parameter and resolution, based on the target bitrate requirements. Although the standard WebRTC implementation does not offer explicit tools for transmitting immersive video, it has gained significant popularity for real-time and ultra-low latency ODV transmission by treating 360° video representation as a conventional 2D video [36], [37]. Additionally, viewport-dependent streaming can be effectively supported by incorporating a combination of high-resolution and low-resolution tiles. This approach optimizes bandwidth utilization while ensuring high quality within the field of view, all while maintaining a low motion-to-photon latency [38].

#### D. Rendering and Display

The human visual system has a limited field of view, which means that users cannot directly perceive the entire 360° content in its spherical representation. Instead, only a portion of the sphere, known as the "viewport," is displayed, which is an image tangent to the sphere. To enhance immersion, interaction with the user is crucial. This interaction can involve head movements (roll, yaw, and pitch), mouse/keyboard controls, or in the case of viewing on a smartphone, the viewing angle can be controlled by moving the device in space, providing a visual experience of up to 3DoF. However, one of the main limitations of ODV is the absence of motion parallax, which refers to the relative position of objects changing based on the viewer's position relative to the object. This limitation can lead to discomfort and sickness for users. To address this limitation, a potential solution is to employ a 360° camera mounted on an UAV. This combination offers enhanced flexibility and mobility, allowing users to explore the environment and move around objects within the scene. By leveraging the mobility provided by the UAV along with the 360° video, a viewing experience of up to 6DoF can be achieved. However, to enable interactive control of the UAV and ensure a more natural viewing experience with accurate control, it is essential to have ultra-low E2E latency (below 100 ms) and high visual quality. These factors are crucial in order to maintain a seamless and responsive interaction between the user and the UAV.

#### E. ODV Streaming Optimization

Several strategies have been proposed in the literature to enhance the QoE in streaming ODV [39]. Depending on the specific application, different metrics can be optimized, including perceived video quality, storage cost, bandwidth usage, and various latency measures (e.g., end-to-end, motion-to-photon, or motion-to-high-resolution/quality latency). Low motion-to-photon latency is particularly important to minimize user discomfort when changing the displayed viewport. Additionally, achieving low end-to-end latency is crucial for live ODV streaming applications, such as UAVs, to enable accurate remote control, especially during high-speed flying conditions. As shown in Figure 2, ODV streaming strategies can be categorized as either viewport-dependent or viewport-independent, depending on whether the field of view is considered in the optimization process or not. The initial streaming approach, commonly used in early literature, involved transmitting the entire 360-degree content at high quality, allowing users to extract the desired viewport based on their head position with ultra-low motion-to-high-resolution latency. This approach aligns with the viewport-independent profiles defined in the OMAF standard. However, it is a bandwidth-intensive solution, requiring over 100 Mbps to transmit an 8K resolution video at high quality [40]. This is inefficient since the end user only observes a small portion (15%) of the ODV. To address this limitation, more advanced techniques have been proposed to provide users with ODV services at high quality and low motion-to-photon latency. In this context, viewport-dependent strategies have gained wide adoption at the projection (projection-based) and encoding (tile-based) stages. The projection-based approach employs dynamic projection methods, such as pyramidal projection and its refined version, offset cubic projection [41]. Offset cubic projection allocates higher pixel density and better quality near the offset direction, which corresponds to the user's viewing direction. Another solution proposed in [37] is oriented projection for real-time 360-degree video streaming using the WebRTC framework. Oriented projection allocates more pixels in the projected frame to areas on the sphere that are close to a target pixel-concentration orientation. This solution is jointly optimized with adaptive resolution and bitrate allocation to accommodate bandwidth variations.

The viewport-dependent OMAF profiles, as outlined in [41], enable independent tile decoding by restricting motion vectors to refer only to the adjacent tile area. This allows the end user to request and decode tiles independently. Following the projection stage, the ODV is encoded into tiles representing different quality representations. The end user can then request the tiles covering the viewport at high quality while the remaining area tiles can be requested at a lower quality. As a result, the tile-based ODV encoding using viewport-dependent OMAF profiles significantly improves the user's QoE and reduces the required transmission bandwidth. However, storing and encoding ODV tiles in multiple representations, each with different rate-quality characteristics, necessitates a large storage capacity and incurs high encoder computational complexity. To address these challenges, the VR Industry Forum

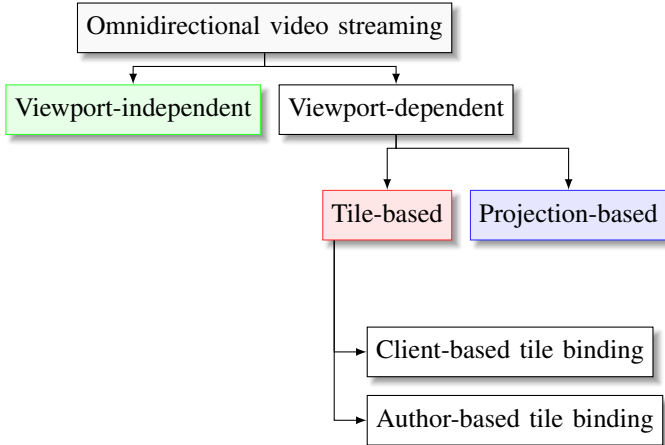


Fig. 2. ODV streaming strategies.

guidelines [42] introduced the HEVC-based FoV Enhanced Video Profile. This profile employs HEVC encoding to achieve low-quality coverage of the entire 360-degree video, while high-quality sub-pictures are encoded to cover specific regions of the video. Each bitstream is then encapsulated within a track compliant with the HEVC-based viewport-dependent OMAF profile. The player can subsequently request the bitstream covering the viewport in high quality, along with the low-quality bitstream representing the entire 360-degree coverage. In live scenarios, the low-quality stream can be transmitted via multicast, allowing for more efficient bandwidth utilization. This approach ensures efficient bandwidth utilization while maintaining ultra-low motion-to-photon latency.

The prediction of end user head movements can be leveraged to enhance the QoE by assigning higher fetching priority to tiles within the predicted viewport. This streaming approach, known as the "human-centric" approach, focuses on optimizing the user experience, in contrast to the "system-centric" approach that prioritizes overall system performance without considering user behavior. The design can be categorized as single-user or cross-users, with the latter considering the behavior of multiple users in predicting the viewport. These techniques rely on accurate viewport prediction models, which are used to optimize the streaming system. In [43], the potential of predicting head movements for optimizing 360-degree video streaming over cellular networks was demonstrated, resulting in up to 80% network bandwidth savings. This approach has been followed by several research papers and commercial products, aiming to optimize network and computational resources while providing users with a highly immersive experience [44].

Finally, Table II depicts the performance of discussed 360° video streaming strategies regarding storage cost, bandwidth usage, motion-to-photon latency, and encoding time.

### III. UAV-BASED REAL-TIME VIDEO STREAMING: PERFORMANCE METRICS

This section focuses on the optimization of wireless networks for real-time video streaming using UAVs, with a particular emphasis on key performance metrics. The discussion

TABLE II  
PERFORMANCE OF STREAMING APPROACHES REGARDING STORAGE CAPACITY, BANDWIDTH USAGE, MOTION-TO-PHOTON LATENCY, AND ENCODING TIME.

	Storage	Bandwidth	Latency	Encoding time
Viewport-indep.	●●●	●●●	●●●	●●●
Projection-based	●●●	●●●	●●●	●●●
Tile-based	●●●	●●●	●●●	●●●

Performance metrics: High ≡ ●●●, Average ≡ ●●●, Low ≡ ●●●

encompasses three essential aspects: latency, video quality, and UAV energy consumption.

#### A. Latency

The latency in video transmission from UAVs significantly impact user's QoE in 360-degree video streaming, including E2E latency. It is captured using several metrics such as motion-to-photon latency, and motion-to-high resolution latency.

**End-to-end latency:** In a point-to-point real-time video transmission, E2E latency plays a vital role in ensuring a seamless and immersive experience. It encompasses the total delay from event capture by the sensor to processing, transmission, and actuator response. The E2E latency between camera and user's display is often referred to as glass-to-glass (G2G) latency. It measures the time difference between when the photons of an event first pass through the camera lens and when the event is displayed to the viewer. Additionally, glass-to-algorithm (G2A) latency represents the time gap between the photon corresponding to an event passing through the camera lens and the availability of the first image corresponding to that event for processing before display. G2A latency is crucial in applications utilizing computer vision algorithms for tasks such as control, object detection, segmentation, viewport prediction, and more. Figure 1 provides an overview of G2G latency and its relationship to G2A latency by removing the latency introduced during the display process.

The overall G2G latency can be expressed as the sum of delays incurred in camera acquisition, encoding, network transmission, decoding, and display processing. Table III presents a breakdown of G2G latency for a state-of-the-art WebRTC-based implementation of an ODV E2E streaming pipeline [45]. This pipeline transmits 8K resolution 360° videos captured using an Insta 360 camera to a Samsung S10 client. The latency breakdown in Table III highlights that the acquisition and stitching process, along with the encoder, contribute to approximately 80% of the total G2G latency. Notably, the latency introduced at the transmitter scales proportionally with the video's resolution. At a high level, the total G2G latency comprises network latency and latency stemming from the transmitter and client components.

Based on the preceding discussion, it can be deduced that reducing latency entails reducing the number of processed



TABLE III  
GLASS-TO-GLASS LATENCY BRAKEUP [45]

Block	Latency (ms)	
Transmitter	Live Streaming	503
	FFMpeg Decoder	568
	360° stitching	28.5
	HEVC encoder	406
	Video packetizer	1.9
	<b>Total latency at transmitter</b>	<b>1508</b>
Client	RTP Packet	79
	Decoder	34
	Renderer	14
	<b>Total latency at client</b>	<b>127</b>
<b>Total G2G latency</b>	<b>1745-1856</b>	

pixels throughout the ODV streaming pipeline, which is primarily determined by the framerate and resolution. Additionally, higher framerates and quality necessitate increased transmission rates, resulting in heavier overheads in terms of transmission delay and transmit power. Conversely, the E2E delay increases when the encoding bitrate fails to adapt to wireless channel variations. As a result, efforts to minimize latency have a direct impact on video quality. Hence, the design of wireless communications for UAV-based ODV streaming predominantly revolves around maximizing video quality while adhering to a latency constraint. Typically, in wireless optimization problems, this latency constraint is imposed as a *delay outage probability* constraint, representing the probability of packet delay exceeding a predefined delay budget. However, it is important to note that the delay outage probability constraint only encompasses queueing and transmission delays, which constitute only a portion of the overall G2G delay.

**Motion-to-photon latency:** In the context of ODV streaming, particularly in viewport-dependent scenarios, it is crucial to consider additional latency metrics that can impact the user’s quality of service. Two such metrics are motion-to-photon (M2P) latency and motion-to-high resolution latency. M2P latency measures the delay required to display the new viewport corresponding to the user’s updated viewing direction after head movement. It encompasses the time needed to request and render the viewport aligned with the user’s viewing direction. The specific streaming approach and the technology of the head-mounted display (HMD) can influence the motion-to-photon latency. Additionally, recent work presented in [46] demonstrates the potential of utilizing head motion prediction algorithms at the end user’s side to significantly reduce the motion-to-photon latency. These algorithms can effectively anticipate the user’s head movements and optimize the rendering process accordingly.

## B. ODV quality

The quality of experience for end users is primarily determined by the perceived video quality and latency. In the context of 2D video, widely used full-reference objective quality metrics include peak signal-to-noise rate (PSNR), structural similarity index measure (SSIM), and video multi-method assessment fusion (VMAF). These metrics provide a comprehensive assessment of the perceived quality by comparing the original and reconstructed videos. However, for 360-degree video content, specialized quality metrics have been proposed to account for the unique geometrical distortions introduced by the spherical representation. Notable examples include Spherical PSNR (S-PSNR) and weighted to spherically uniform PSNR (WS-PSNR), which are full-reference objective quality metrics specifically developed for 360-degree video content [47].

As mentioned earlier, video quality is influenced by various factors, including encoding bitrate, frame resolution, frame rate, and the characteristics of the air-to-ground wireless channel. Generally, higher quality and lower distortion can be achieved by using a higher bitrate (or resolution) and benefiting from favorable channel conditions. Consequently, selecting a higher video bitrate is preferable for improved video reconstruction quality. However, it is important to note that bitrate selection not only affects video quality but also impacts latency. A higher bitrate necessitates a more stringent throughput requirement, posing challenges for efficient wireless resource allocation. Therefore, when designing the system, a trade-off must be considered between reconstruction quality/distortion and bitrate selection, while optimizing the provision of wireless resources to meet the selected video bitrate.

## C. UAV Energy consumption/ Flight Time

UAVs are frequently required to maneuver in three-dimensional space to perform various monitoring and video streaming missions. One crucial consideration in UAV-based ODV streaming systems is the energy consumption of UAVs due to their limited energy budget. The energy consumed by a UAV during movement is referred to as “propulsion energy,” which is influenced by the UAV’s velocity and acceleration. Moreover, when the UAV hovers at a fixed position while streaming the video, it consumes “hovering energy” [48], [49]. Furthermore, as discussed below, the air-to-ground channel between the UAV and the ground user is implicitly affected by the UAV’s position in the 3D space. For example, the small-scale fading component of the UAV-ground wireless channel can be modeled as an “angle-dependent Rician fading channel” with the Rician factors directly proportional to the UAV-ground elevation angle [50]. This model captures the fact that as the elevation angle increases, the UAV-ground link tends to experience less scattering, resulting in a larger line-of-sight (LoS) component. On the other hand, the large-scale fading component, which includes path loss and shadowing, depends not only on the 3D locations of the UAV and the ground user but also on the geographic distribution of buildings. In urban areas, the signal propagation of a UAV flying at a

lower altitude may be obstructed by buildings, leading to the shadowing effect [51]. In contrast, when the UAV transmits at a higher altitude, it only experiences path loss without any shadowing. However, conducting a comprehensive path-loss measurement for a wide geographic area is infeasible. Therefore, a generic probabilistic aerial-to-ground channel model that statistically incorporates both LoS and non-line-of-sight (NLoS) large-scale fading is considered in [52]. In this model, the probability of experiencing LoS path loss increases as the UAV raises its altitude or moves closer to the ground user horizontally.

In conclusion, the trajectory and position of a UAV have an impact on its energy consumption and the quality of the transmitted video. Hence, in the deployment and trajectory design of UAVs for video streaming, the distinctive features of the air-to-ground channel, as well as the propulsion and hovering energy consumption, must be carefully taken into account. The following section provides a more detailed exploration of these design challenges and discusses the current state-of-the-art in each aspect.

#### IV. WIRELESS COMMUNICATIONS DESIGN FOR UAV-BASED REAL-TIME VIDEO STREAMING

This section provides a comprehensive survey of the ongoing research efforts in the design and optimization of wireless communications for real-time video streaming systems using UAVs. Additionally, we also review the relevant standardization activities conducted by 3GPP.

##### A. Quality of Experience Maximization

To meet the demanding requirements of real-time transmission in high-resolution video streaming systems with superior QoE, UAV-based ODV streaming systems impose stringent criteria on both throughput and latency performance. The latency of such systems is typically characterized by E2E latency or photon-to-motion latency. The inherent randomness of wireless channels poses a significant challenge in achieving desired QoE, as fluctuating channel conditions result in unpredictable latency, leading to interrupted or choppy video streaming. Maximizing QoE is generally approached as a problem of maximizing PSNR through optimizing wireless resource allocation, including transmit power, rate, or bandwidth, while adhering to various wireless network and UAV-imposed constraints. In this section, we survey the state-of-the-art advancements in this area. We note that most of the literature in this area has focused only on transmission of 2D videos from UAVs.

One notable work by Xia *et al.* [53] utilized the internal sensor data of the UAV for adaptive bitrate selection. They leveraged location, velocity, and acceleration information to predict future throughput and proactively select the video bitrate accordingly. The performance evaluation, conducted using a laptop on the ground and the DJI Matrice 100 drone with an attached Android smartphone in an outdoor environment, employed the IEEE 802.11n protocol. The simulations demonstrated that the selected bitrates effectively adapted to future throughput, maintaining relatively stable video bitrates

over time, resulting in a seamless video viewing experience despite channel fluctuations. In another study, Muzaffar *et al.* [54] focused on a multicast video streaming framework where a UAV delivers video to ground users. The proposed approach incorporated feedback from the users to dynamically adjust the transmission rate and video bitrate. The performance evaluation, conducted using the AscTec Pelican drone equipped with a Logitech C920 camera and employing the IEEE 802.11a protocol and AVC/H.264 video format, investigated throughput, packet loss, and delay. The rate-adaptation approach demonstrated improvements in throughput, latency, and packet loss compared to a constant transmission rate and bitrate baseline, resulting in up to 30% PSNR gain. These works represent significant advancements in enhancing QoE through adaptive bitrate selection and rate control mechanisms, showcasing the potential of optimizing wireless communications in UAV-based video streaming systems.

In [55], the authors addressed the transmission rate allocation problem in a UAV video streaming system, where multiple UAVs transmit their captured videos to different users. The objective was to minimize the overall reconstruction error of all users by optimizing the transmission rates, subject to the total network channel capacity. The performance evaluation, conducted using PSNR as a measure of video reconstruction quality, showed that the proposed rate allocation approach achieved a 6 dB gain over the equal allocation baseline. Extending the system model in [55], [56], considered a multi-UAV setup, where UAVs competed for transmission rates by incurring a cost to obtain higher rates. Each UAV aimed to maximize its utility, comprising PSNR and cost, by selecting a transmission rate within the network capacity budget. The authors designed a rate allocation algorithm using game theory to address the rate competition among UAVs. Compared to the equal bandwidth allocation baseline, the proposed algorithm increased network utility while considering video quality requirements. In contrast to adapting the bitrate to match the channel fluctuations, another stream of work [57], [58] attempts to maximize the PSNR by using an scalable video coding (SVC) based video transmission. In SVC, the video is encoded into a base layer and  $N$  enhancement layers. If the  $n$ th quality is selected for the streamed video, the base layer and all lower enhancement layers, i.e.,  $1, \dots, n-1$ , have to be delivered along with the  $n$ th layer [57]. Note that more enhancement layers give the better quality of the received video, i.e., the higher PSNR, but require more transmit power at the UAV. In [57], Zhang *et al.* considered a system where a UAV transmits video to a terrestrial BS with SVC. The objective was to maximize the energy efficiency maximization subject to the *delay outage probability* constraint, i.e., the probability that packet delay exceeds a predetermined delay budget. Energy efficiency is defined as the ratio of the PSNR to the total power. The optimal solution jointly determines the number of enhancement layers and transmit power. In contrast with the baseline, which randomly selects the number of layers and power, the proposed approach improved the energy efficiency by 40% and decreased the delay outage probability from 0.3 to 0.05. The work [58] studied a video streaming system in which the base and enhancement layers of



the SVC video are sent from a terrestrial BS and the UAV BSs with the storage and computation capabilities to the ground users. Each layer of the video can be served by either the terrestrial BS or a UAV BS, i.e., the user obtains the layers of the video from various BSs. The computation capabilities at the BSs can be used for video processing, e.g., encoding the video's base layer and enhancement layers. In addition, the UAVs without the storage and computation capabilities act as relays to help the transmission from the terrestrial BS to the users. Since the number of enhancement layers affects the video quality, the users desire more enhancement layers. By optimizing over the transmit power and allocated bandwidth of the BS and UAVs, the numbers of enhancement layers for the users, the video layer assignment (i.e., from which BS), and the 2D deployment of the UAVs, the objective in [58] was to maximize the sum of all users' QoE metrics, e.g., normalized PSNR, subject to the constraint on the transmission and computation delays. The proposed approach achieved 15% better QoE, i.e., received video quality improvement, than a baseline, where the video layers for the user originate from a single BS delivering the highest throughput. In contrast with the other baselines in which the video layers for all users originate from the terrestrial BS, and the video transmission is helped by the UAV relays, the proposed approach could achieve 68% QoE further enhancement. Nevertheless, due to its high computational complexity requirements and lack of broad support by consumer devices, the SVC based approach is not preferable for real-time video transmission.

### B. UAV Deployment and Trajectory Design

In addition to wireless resource allocation, such as transmit power and bandwidth, the maneuverability of UAVs offers an additional dimension for enhancing video streaming performance, including throughput and latency. By optimizing the UAV's location or trajectory in three-dimensional (3D) space, both energy consumption and wireless channel conditions can be improved.

Guo *et al.* [59] focused on the 3D trajectory design of a UAV deployed to inspect multiple facilities and transmit real-time video to a control center. The objective was to minimize the total energy consumption associated with propulsion and hovering. The trajectory between successive facilities directly impacted propulsion energy, while hovering energy depended on the inspection time at each facility, determined by video bitrate and transmission latency. Therefore, a trajectory planning algorithm was proposed in [59] to minimize total energy consumption, assuming a fixed video bitrate. Simulation results demonstrated that the proposed algorithm significantly reduced the UAV's energy consumption and flight time. Moreover, resource allocation in terms of time slots, transmit power, and transmission rate was studied in [60], where a UAV delivered videos to multiple ground users. The trajectory design took into account the propulsion energy consumption. Building upon the work in [59], Bur *et al.* [61] extended the research to collaborative inspection of a fire area by multiple UAV-users, with the inspected videos sent to a UAV-BS. The optimization involved the transmit power of all UAVs, 3D

trajectories of UAV-users, and dynamic bitrates of the users' inspected videos. The focus was on QoE maximization, which accounted for transmission delay violation and the normalized transmission rate based on the selected video bitrate. Additionally, the transmission rate needed to be sufficient to support the selected video bitrate, considering the trajectories and transmit power of the UAVs. The proposed approach enabled the support of 720p and 1080p videos with an average delay of 0.05 ms, whereas a greedy approach relying on immediate QoE decisions only supported 140p video with an average delay of 1.2 ms. Overall, these studies highlight the importance of optimizing UAV trajectories and resource allocation to enhance video streaming performance, achieving energy efficiency, reduced delay, and improved QoE.

Furthermore, Khan *et al.* [62] investigated a UAV-to-UAV communication network where UAVs collaboratively streamed video to a ground server. Their approach involved utilizing dual paths for transmitting SVC video with one enhancement layer. The base layer is sent directly from a UAV to the ground server via a radio frequency link, while the enhancement layer is relayed to the server by neighboring UAVs using free-space-optical links. The objective was to minimize distortion in the received video by jointly optimizing the bitrates of the base and enhancement layers, the routing path, and UAVs deployment. The optimization was subject to a constraint on propulsion energy consumption and the channel capacity's bitrate limitations. The proposed approach achieved an average PSNR gain of 6 dB compared to a baseline approach that used dual paths with only radio frequency links, without optimizing the routing path and UAVs deployment. In another study, Zhang *et al.* [60] formulated the user's utility as the normalized transmission rate relative to a predetermined bitrate (considering fairness among users). They aimed to maximize the lowest time-averaged utility among all users by jointly designing trajectories and allocating wireless resources. The proposed approach outperformed three baselines: trajectory optimization, wireless resource optimization, and no optimization. It achieved up to a 3-fold increase in transmission rate. In summary, Khan *et al.* explored UAV-to-UAV communication networks, demonstrating the benefits of jointly optimizing routing paths, UAVs deployment, and bitrate allocation for enhanced video streaming performance. Zhang *et al.* focused on maximizing users' utility through joint trajectory design and resource allocation, achieving significant improvements in transmission rates compared to various baselines.

### C. Control Command and Video Data Coexistence

In the context of UAV teleportation, the operator at a remote location guides the UAV to perform critical missions using the live video feed. This involves simultaneous uplink streaming of real-time video and downlink delivery of control commands. Achieving high-quality video streaming necessitates high throughput and low latency, while delivering control commands requires ultra-reliable and low-latency communication. Hence, in wireless systems designed for UAV teleportation, ensuring reliable and low-latency control command delivery, as well as optimal throughput and latency performance for

video streaming, becomes crucial. In the following sections, we examine recent testbed setups that addressed the co-existence of control command and video data, focusing on reliability and latency performance.

Stornig *et al.* [63] employed the ns-3 network simulator to study E2E delays and video quality metrics (PSNR and SSIM) in video streaming over 4G networks. They modeled the UAV's 3D trajectory using a Gauss-Markov mobility model, and the video traffic was simulated using the MPEG-4 format with the Evalvid application. The impact of UAV mobility on latency performance was thoroughly examined. Simulation results indicated that approximately two-thirds of frames were received with good or excellent quality, while 27% of frames in regular mobility and 30% of frames in high mobility exhibited inferior quality. Moreover, the average PSNR and SSIM values for the received video were 33 dB and 0.945, respectively, indicating good quality.

In the testbed presented in [64], a DJI Matrice 100 drone equipped with the Quectel EC25 Long Term Evolution (LTE) module and a Raspberry Pi camera were utilized. A computer with a USRP B210 radio frequency unit served as the BS, connected to the remote controller via a wireline connection. The experiments were conducted indoors using the AVC/H.264 video standard. Various metrics were evaluated, including transmission delay, packet loss probability of control commands, and video data throughput. The results demonstrated that when the control command was updated less than 40 times per second, the command delivery experienced a 20 ms transmission delay without any packet loss. Furthermore, the average delay and throughput for 480p and 720p video resolutions ranged from 1.5 s to 5.5 s and from 2 Mbps to 9 Mbps, respectively. In [65], the authors evaluated the performance of a testbed equipped with the Huawei MH5000 5G module, operating in an outdoor environment. The transmission rates for streaming 1080p video in HEVC/H.265 format over 4G and 5G networks were measured at 16 Mbps and 97 Mbps, respectively. The G2G delays were evaluated as 1.2 s and 3 s for the respective networks. Additionally, the E2E delay of control command delivery was measured to be 30 ms in the 5G network. In a different study, [66], an immersive UAV control testbed was implemented using the Oculus Quest 2 HMD to control UAV movement and FoV over 4G, 5G, and WiFi networks. The Insta360 One X camera captured 360° video, and streaming rates of 2 Mbps to 8 Mbps were considered, investigating various delays: G2G delay, glass-to-reaction-to-execution delay, and sensor reaction delay. The G2G delay ranged from 0.595 s to 0.985 s, the glass-to-reaction-to-execution delay ranged from 0.89 s to 1.38 s, and the sensor reaction delay ranged from 0.67 s to 1.12 s as the streaming rate varied 2 Mbps to 8 Mbps. The control command transmission delay was measured at 138 ms, 103 ms, and 88 ms for 4G, 5G, and WiFi networks, respectively. Additionally, the PSNR quality of the received video for 720p and 4K resolutions ranged from 30 to 47 dB.

#### D. Wireless Network Architecture

Based on the aforementioned quality factors, the design of wireless systems for UAV-based video streaming can vary

depending on the specific wireless network architectures employed. Each network architecture comes with its own restrictions, advantages, overheads, and hardware requirements, leading to diverse performance outcomes. However, poor performance can significantly hinder the feasibility of real-time UAV video streaming. Therefore, it is crucial to incorporate practical and distinct features that evaluate video streaming quality and UAV communication performance in the design of wireless systems for UAV-based video streaming. The evaluation outcomes can also serve as guidance for selecting the appropriate network, depending on the application requirements of UAV-based video streaming.

In previous works, such as [67], [68], the network simulator ns-3 was utilized to investigate the performance of UAV video streaming in 4G networks. The Evalvid application was employed to simulate the video transmission from the UAV to the BS using MP4 format videos. The study in [67] primarily focused on throughput investigation in both outdoor and indoor environments. In the outdoor scenario, the average throughput achieved by a static macrocell UAV was found to be 60 kbps, while the throughput decreased to 20 kbps as the UAVs moved at speeds ranging from 1 to 5 m/s. In the indoor environment, the improvement in throughput was more significant for multi-story buildings with an increased number of deployed femtocell BSs.

Naveed *et al.* [68] explored the relationship between the reference signal received power (RSRP) and throughput. Their findings revealed that as the RSRP varied from -110 dBm to -75 dBm, the UAV achieved video streaming throughputs ranging between 2 kbps and 80 kbps. Additionally, the authors evaluated the received video quality using PSNR and SSIM scores under various wireless channel conditions. The PSNR scores were observed to be 49.41 dB, 35.42 dB, and 24.31 dB in the best, good, and poor channel conditions, respectively. Similarly, the SSIM scores were found to be 0.99, 0.63, and 0.35 in the respective channel conditions. Furthermore, the impacts of different channel conditions on video quality were visually highlighted through sample videos.

In another study by Sinha *et al.* [69], the network simulator ns-2.29 was employed to evaluate the throughput, packet loss, packet retransmission, and E2E delay performance of video streaming between UAVs and from the UAV to the ground control station in different network configurations, including wireless local area network (WLAN), WLAN router, WiFi hotspot, and WiFi Direct. Results indicated that WiFi Direct achieved the best performance for all metrics, followed by the WiFi hotspot, while the WLAN network exhibited the poorest performance in all considered metrics.

The performance evaluation of multi-path video streaming in 4G networks was conducted in the works by Liu & Jia [70] and Nihei *et al.* [71]. In the testbed presented in [70], video data was transmitted from dual devices inside the UAV to a smartphone. The dual-stream approach employed in this study demonstrated the capability to reduce the E2E delay to approximately 50 ms, contrasting the single-stream approach. In an independent study, Nihei *et al.* [71] tested the multi-path video streaming method in 4G networks by distributing the video data over two 4G mobile network operations in

Indonesia. The objective of data splitting was to minimize the average E2E delay. The experimental setup involved the use of a DJI Spreading Wings S800 drone equipped with a Raspberry Pi camera. Outdoor experiments were conducted using the AVC/H.264 format, demonstrating the ability to adapt the video data to network throughput. Visual illustrations provided in the study showcased the quality improvement achieved with the multi-path method, highlighting its potential suitability for forest fire surveillance. The performance of 60 GHz mmWave for video transmission was evaluated by Yu *et al.* [72]. In their experiment conducted in an outdoor environment, a 4K uncompressed video was transmitted from the UAV to a nearby server to offload further computations. The testbed achieved a throughput of 1.65 Gbps, and the results indicated that offloading computations to the server enabled the UAV to save 271.8 watts in computations at the expense of 4.1 watts for mmWave communication. In contrast to the aforementioned studies, Hu *et al.* [73] conducted a numerical analysis of a UAV-based ODV streaming system, where ground users requested specific video tiles within their FoV from the UAVs. The UAV then transmitted the requested tiles to the users via associated access points (APs), which acted as decode-and-forward relays. These APs collaboratively broadcasted the video data to the corresponding users. The objective of their approach was to maximize the PSNR by scheduling time slots to the UAVs and associating them with the APs. The proposed approach yielded an enhancement in PSNR compared to baselines where each AP worked independently or all APs worked together.

It is worth noting that while the majority of the studies discussed in this section focused on non-real-time video streaming, they offer valuable insights into the design of UAV-based real-time ODV streaming. For example, the work by Yu *et al.* [72] emphasizes the importance of joint communications, computation, and control design for UAV-based real-time video streaming. Similarly, the results presented in [70], [71] demonstrate the effectiveness of multi-path streaming in significantly reducing E2E delays. Furthermore, the aforementioned studies shed light on the impact of various network settings on video streaming performance.

#### E. Overview of Relevant 3GPP Standardization Activities

The standardization activities related to UAV-based immersive video streaming within the 3GPP can be divided into two main categories. The first category involves the integration of UAVs with cellular networks, while the second category focuses on 5G support for media streaming applications, such as augmented reality, virtual reality, and real-time communication. In the following sections, we provide a comprehensive overview of the recent advancements and state-of-the-art developments in these two areas.

1) *Communication for UAVs*: To evaluate the potential of LTE networks in supporting UAVs through cellular connectivity, the 3GPP initiated the Release 15 study in March 2017 [74]. The findings of this study are documented in TR 36.777 [75]. The study revealed that the line-of-sight signal propagation in UAV communications increases the likelihood

TABLE IV  
SUMMARY OF 3GPP RELEASE 18 ACTIVITIES FOR SUPPORTING MEDIA STREAMING ON 5G NETWORKS

3GPP Document	Focus
TS 26.501 [79]	5G Media Streaming (5GMS); General description and architecture
TS 26.506 [80]	5G real-time media communication architecture
TS 26.522 [81]	5G real-time media transport protocol configuration
TS 26.803 [82]	Study on 5G media streaming extensions for edge processing
TR 26.927 [83]	Artificial intelligence and machine learning in 5G media services

of severe interference in both uplink and downlink scenarios. Consequently, various interference detection and mitigation solutions were proposed as study items and work items. Additionally, solutions related to mobility information management and aerial user identification were put forth. In Release 16, the focus shifted towards investigating the feasibility of remotely identifying UAVs [76]. In Release 17, 3GPP further addressed the operational 5G support of UAVs by providing functionalities for UAV authentication, authorization, and tracking [77]. Moreover, it allows for command and control authorization.

2) *Support for Media Streaming over 5G*: The support for virtual reality (VR) over wireless networks was initiated in 3GPP Release 15 with the publication of TR 26.918 [78]. This report aimed to identify the potential gaps and use cases for facilitating virtual reality (VR) services over wireless networks. In addition, Release 17 TS 26.118 introduced operation points, such as resolution and color mappings, and defined media profiles for the distribution of VR content. To address the challenges associated with real-time immersive media streaming, Release 18 of 3GPP is currently investigating several relevant issues. For a comprehensive overview of the activities under Release 18, please refer to Table IV.

## V. DATASET DESCRIPTION

As mentioned earlier, the utilization of visual attention and saliency information can provide valuable insights into human visual scene analysis patterns. This knowledge can be harnessed to develop effective encoding and streaming methods. Visual attention and saliency information can be derived by analyzing viewers' head movement (HM) and eye movement (EM) during video playback. In this section, we present a comprehensive survey of existing EM and HM datasets for ODV captured by UAVs. Additionally, we introduce a new dataset that we have curated for this study.

In the existing literature, several works have introduced datasets focused on ODV, encompassing EM and HM information of viewers [88]. For better understanding the user behavior while watching ODVs, these datasets categorize the ODVs, based on the number of moving objects and camera motion, and include users' feedback about viewing experience [89]. On the other hand, [90] classified the videos based on their genre, such as documentary, movie, etc. The majority of these datasets consists of videos with 3DoF which makes

TABLE V  
SUMMARY OF EXISTING DATASETS

Dataset	Resolution	Frame rate	Dimension	Description
EyeTrackUAV2 [84]	1280 × 720 and 720 × 420	30 fps	2D	Eye tracking data
AVS1K [85]	1280 × 720	30 fps	2D	Eye tracking data
WinesLab [86]	1080 × 1920	30 fps	360°	Videos recorded using both handheld and UAV mounted camera
360 Track [87]	3840 × 2160	30 fps	360°	Includes the ground truth for tracking
Proposed	3840 × 2160	30 – 50 fps	360°	Table VI

them less suitable for learning the user viewing pattern for a UAV based ODV streaming protocol. Indeed, inferences obtained using ODV with 3DoF may not be applicable for video transmission platforms with 6DoF, such as UAV based ODV transmission. This raises the need to develop novel datasets of ODVs captured using UAVs. In the following, we briefly survey the existing datasets based on the videos captured from UAVs.

While many datasets in the literature include images and 2D videos captured by UAVs for applications such as remote sensing and navigation, only a limited number of publicly available datasets capture EM and HM information for UAV-recorded videos, with only one dataset currently accessible [86]. Similarly, there is only one dataset available for UAV-based 360° videos. We summarize these datasets in Table V. The EyeTrackUAV2 dataset [84] collects binocular gaze information from 30 viewers watching 43 2D videos under both free viewing and task conditions. The AVS1K dataset comprises ground truth salient object regions for 1000 videos observed by 24 viewers in free viewing conditions. The WinesLab dataset contains 11 360° videos, seven of which were recorded by a pedestrian using a handheld camera, while the remaining four were captured using a drone-mounted camera in various surroundings and lighting conditions. The 360Track dataset consists of 9 360° videos with manually marked ground truth positions of salient objects. Additionally, we describe in the following our dataset of *aerial* 360° videos presented in Table VI.

The dataset presented in Table VI comprises a total of ten 360-degree videos. The resolution for all videos, except for “FreeStyleParaGliding,” is 3840 × 1920, while “FreeStyleParaGliding” has a resolution of 5120 × 2560. Each video sequence in the dataset has a length of 40 seconds. The majority of videos, except for “DubaiVertical” and “AbuDhabiCity,” have a frame rate of 30 frames per second (fps), whereas “DubaiVertical” and “AbuDhabiCity” consist of 50 fps. The dataset consists of five outdoor videos, one sports video, and one video recorded in night time conditions. The “NorthPoleTrip” video captures motion in the azimuth plane, while the “DubaiVertical” video captures motion in the elevation. Lastly, all video sequences are encoded and transmitted using the ERP representation.

## VI. BENCHMARK AND ANALYSIS

In this section, we first perform a comprehensive performance benchmarking of five video coding standards

TABLE VI  
SUMMARY OF OUR DATASET

Sequence Name	Spatial Resolution	#Frames	Frame rate (fps)	Scene Feature
PetraJordan	3840 × 1920	1200	30	Outdoor
CapeTownCityPenorama	3840 × 1920	1200	30	Outdoor
CapeTownCityBeach	3840 × 1920	1200	30	Outdoor
CapeTownCityGarden	3840 × 1920	1200	30	Outdoor
CapeTownCitySquare	3840 × 1920	1200	30	Outdoor
FreeStyleParaGliding	5120 × 1920	1200	30	Sports
StPetersBergMuseum	3840 × 1920	1200	30	Night
NorthPoleTrip	3840 × 1920	1200	30	Motion
DubaiVertical	3840 × 1920	2000	50	Vertical Motion
AbuDhabiCity	3840 × 1920	2000	50	City Panorama

TABLE VII  
PARAMETERS OF USED ENCODING WORKSTATION

<b>CPU</b>	Intel Xeon Silver
#cores	8
Max Freq (GHz)	3.9
RAM	32 GB
SSD	256GB
<b>GPU</b>	NVIDIA Ampere RTX A5000
<b>Operating System</b>	Ubuntu 20.04

and formats (i.e., AVC/H.264, HEVC/H.265, VVC/H.266, AV1, and VP9) through their software implementations: libx264, libx265, fraunhofer versatile video encoder (VVenC), libvpx-vp9, and libsvtav1, respectively. We also considered two NVIDIA hardware encoder designs hevc\_nvenc and avc\_nvenc, for the AVC/H.264 and HEVC/H.265 standards, respectively. All encoders are configured in their fastest preset, targeting live 360° video streaming applications. Table VIII gives the used hardware and software encoder libraries for the five standards and formats. The encoding process was deployed on a DELL precision 7820 tower workstation. This later is equipped with an Intel Xeon CPU with 8 cores running at a maximum frequency of 3.9 Ghz and a NVIDIA RTX A5000 GPU. Furthermore, we present a real test-bed for real-time drone ODV streaming using a hardware AVC/H.264 encoder and WebRTC streaming protocol, enabling remote UAV control and navigation with 6DoF viewing experience.

### A. Coding and complexity performance

This section evaluates the coding performance and speedup of the considered software and hardware encoders on video

contents captured by a UAV. The quality of decoded 360° videos is assessed using three objective quality metrics: Spherical PSNR (S-PSNR), SSIM, and VMAF. The videos are encoded at four practical UAV target bitrates of 1.5 Mbps, 3 Mbps, 4.5 Mbps, and 5.8 Mbps, enabling the computation of the BD-rate performance. The BD-rate gives the average bitrate saving or loss compared to the anchor encoder over the four considered bitrates.

Figures 3(a), 3(b), and 3(c) provide the average quality performance of the studied software and hardware video encoders on the proposed dataset, utilizing three distinct quality metrics: S-PSNR, SSIM, and VMAF, respectively. From the results, it is evident that the AV1 software encoder achieves the highest quality in terms of S-PSNR and VMAF across all four bitrates. Following closely is the VVenC software encoder, which demonstrates competitive performance with AV1, particularly at high bitrates, based on the SSIM metric. On the other hand, the libx264 software encoder reports the lowest quality among the tested encoders. It is worth noting that the hardware design for the AVC/H.264 standard outperforms the libx264 software encoder significantly across all quality metrics and bitrates. Interestingly, the software implementation of the HEVC/H.265 standard exhibits slightly higher quality than its hardware implementation. This can be attributed to the increased complexity introduced by the new tools in the HEVC/H.265 standard, making the design of a hardware encoder for HEVC more challenging compared to the AVC/H.264 standard.

The associated BD-rate results with respect to the AVC/H.264 software encoder for S-PSNR, SSIM, and VMAF are depicted respectively in Figures 4(a), 4(b) and 4(c), plotted versus the encoding time. These figures reveal that the hardware encoders (h264\_nvenc and h265\_nvenc) and the AV1 software encoder offer the best tradeoff between coding efficiency and encoding time. Notably, only the hardware encoders can achieve real-time encoding at 30 frames per second. To achieve real-time encoding, the AV1, AVC, and VP9 software encoders would require a powerful processor with multiple cores operating at a higher frequency. In contrast, the VVC/H.266 software encoder (VVenC) exhibits significantly longer encoding times, taking more than one hour to encode a 10-second video. The new coding tools introduced in the VVC/H.266 standard have expanded the search space for rate-distortion optimizations, leading to increased encoding complexity. To enable real-time capability, advanced algorithmic optimizations, along with more efficient low-level optimizations, are necessary. Furthermore, the development of efficient hardware designs for the VVC/H.266 standard becomes crucial, particularly for low-energy embedded devices, to achieve real-time encoding and benefit from its high coding efficiency and advanced features for ODV contents.

### B. Testbed for UAV 360° Video Streaming

The proposed testbed comprises essential components, namely a UAV equipped with a 360-degree camera, a 5G modem, and an edge server. The 360-degree camera captures a comprehensive view of the surroundings, providing an

TABLE VIII  
VIDEO ENCODER SW/HW LIBRARIES

Video codec standard	Software	Version	Hardware
AVC/H.264	libx264 [91]	0.164.3106	h264_nvenc [92]
HEVC/H.265	libx265 [93]	3.5+1-f0c1022b6	hevc_nvenc [94]
VVC/H.266	VVenC [95]	1.7.0	-
AV1	libsvtav1 [96]	1.4.1	-
VP9	libvpx-vp9 [97]	1.11.0-30-g888bafc78	-

immersive 3DoF viewing experience that ensures no critical details are overlooked during acquisition. The 5G modem enables real-time transmission of high-resolution footage from the UAV to the edge server. Users can connect to the edge server through a HMD at the command center, facilitating prompt decision-making by providing immediate access to live 4K 360-degree video footage.

Figure 5(a) depicts the field tests conducted with a First Person View (FPV) UAV operator controlling the UAV in a desert environment. The operator sends commands to the UAV through a central server located 100 km away from both the UAV and the operator. Both the UAV and the operator are connected to a consumer 5G network, as shown in Figure 5(b), with specific settings outlined in Table IX. During the experiment, the operator flew the drone at a fixed position while varying the altitude. Simultaneously, the onboard computer of the UAV recorded information received from the 5G modem, including the Cell ID, throughput, and network latency from the UAV to the central server.

Figures 6(a) and 6(b) provide insights into the flying conditions for handovers and the instantaneous throughput as a function of altitude in the scenario of vertical landing of the drone. In Figure 6(a), it can be observed that the drone experienced a total of ten handovers, utilizing the four available base stations that cover the flying area. Figure 6(b) shows that most of the handovers resulted in improved instantaneous throughput. However, the throughput exhibited significant fluctuations due to wireless communication instability and interference.

At higher altitudes, the drone encounters interference from base stations primarily designed for ground-based users. This interference introduces latency and quality degradation in the transmission of video and control signals, thereby posing challenges for effective drone navigation by the operator. Our real field tests showcase the control of UAV through 5G using a VR headset and 360-degree video feedback at altitudes of up to 600 meters. These tests shed light on the potential challenges associated with interfering base stations and suboptimal handover conditions in VR-based UAV control.

## VII. OPEN CHALLENGES

### A. Adaptive Low-latency 360° Video Streaming

From Figure 6(b), it is evident that UAV communication, particularly at high altitudes and during mobility, is susceptible to significant throughput variation. This inherent issue raises fundamental concerns regarding the attainment of high QoE with superior video quality and minimal G2G latency in real-time 360-degree video streaming. To address these challenges,

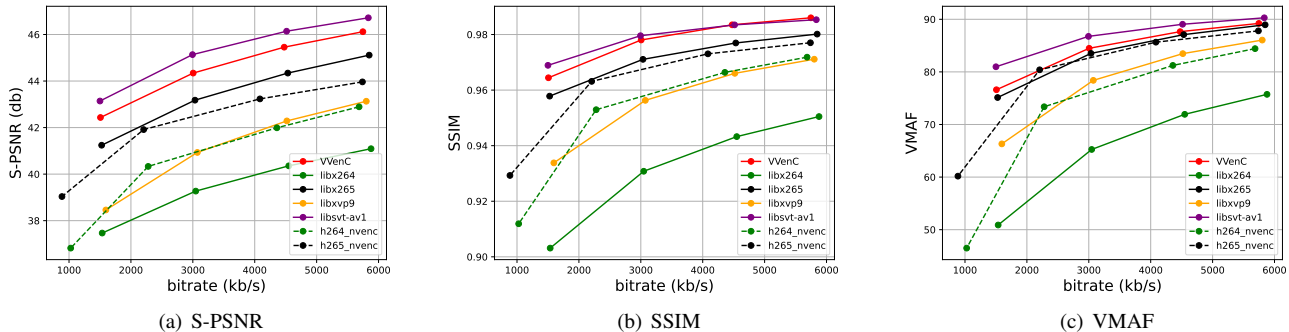


Fig. 3. The average quality in S-PSNR (dB), SSIM and VMAF at different bit-rate for the seven considered encoders.

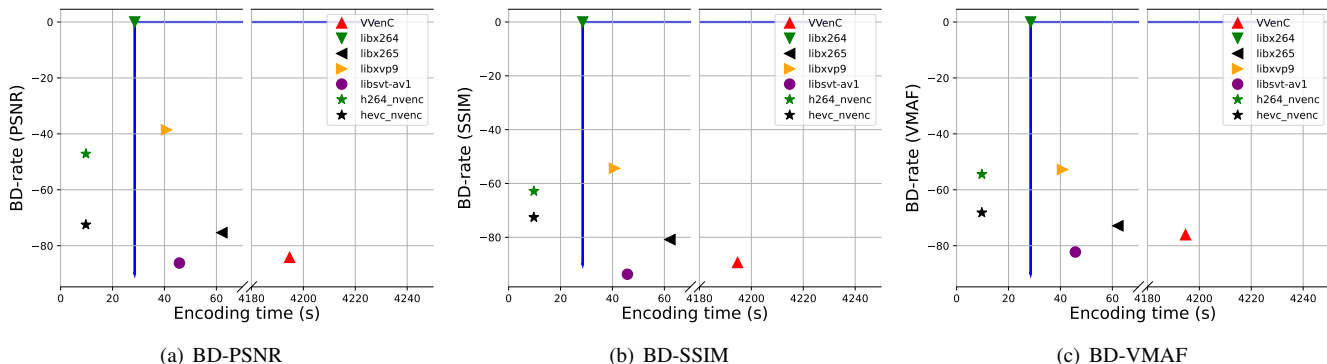


Fig. 4. The BD-rate performance in S-PSNR (dB), SSIM and VMAF versus encoding time for the seven considered encoders on 10 seconds video contents.

TABLE IX  
CONFIGURATION OF THE 360° VIDEO STREAMING OVER UAV TESTBED.

Parameter	Value
5G Max(upload/download)	50 Mbps/100 Mbps
Server CPU	8 cors @ 2.5 GHz
Server memory	16 Gb
Distance UAV to Server	500m
Distance VR HMD/UAV to Server	100km
UAV flight speed during tests	25Km/h
UAV's onboard computer	Jetson nano
UAV's weight	2.5 Kg
360-degree camera	Ricoh Theta Z1

several open research directions can be pursued. Firstly, leveraging the latest video coding standards and efficient hardware encoders, such as hevc\_nvenc, can substantially enhance perceived video quality. The hevc\_nvenc encoder enables real-time encoding with low energy consumption, harnessing the coding efficiency promised by the advanced video coding standard, HEVC/H.265. This, in turn, extends the UAV's battery life. At the cloud level, more efficient software encoders like SVT-AV1 can be utilized for video transcoding, leveraging the available cloud resources. Furthermore, advanced optimization techniques, such as FoV prediction, can be employed to allocate higher quality to the viewing viewport, resulting in improved bandwidth utilization and perceived video quality for end-users.

Secondly, ensuring fast and accurate adaptation of the video bitrate to channel throughput variations is crucial to prevent

buffering at both the transmitter and receiver sides, thereby minimizing G2G latency. In this regard, leveraging information from the physical layer as well as the UAV status, position and its environment can be valuable for predicting throughput variations and facilitating proactive encoder adaptation. Additionally, jointly considering other source video parameters, such as spatial resolution, temporal frame rate, and projection, in the rate control mechanism can further minimize G2G latency and maximize perceived quality. Advanced machine learning techniques, including deep reinforcement learning, have demonstrated potential in learning real-time prediction of pre-processing and encoder parameters to achieve the target bitrate while maximizing perceived quality [98], [99].

Finally, these research directions pave the way for addressing open challenges in UAV-based 360-degree video streaming, leading to improved QoE, minimized latency, and enhanced video quality.

### B. Cooperative Aerial Video Streaming

Cooperative immersive video streaming, exemplified by Intel's Trueview [100], has the potential to enable a truly immersive viewing experience [101]. This approach allows users to independently select their preferred viewing angle by streaming from multiple cameras or sources, leveraging spatial diversity in terms of viewing angle, content, or geographic location. Moreover, employing multiple UAVs to capture aerial views can enhance the immersive experience with



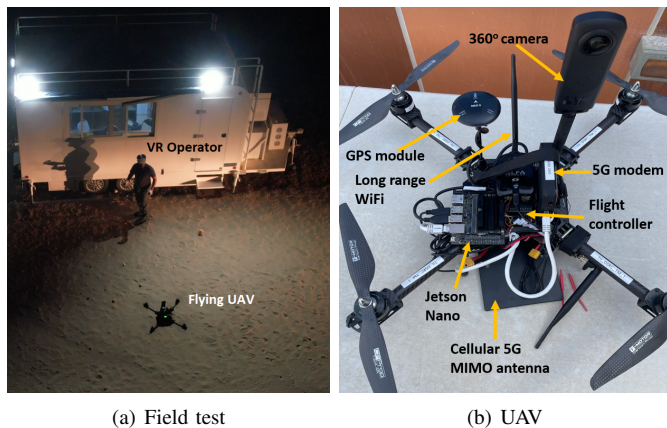


Fig. 5. Illustration of the field test setting and the UAV configuration.

6DoF capabilities [102], [103]. However, developing a multi-UAV cooperative immersive video streaming system entails addressing a unique set of challenges in joint communication, computation, and control design. Streaming a scene captured by multiple UAVs requires effective coordination among the UAVs to ensure comprehensive scene coverage without compromising QoE while minimizing network bandwidth usage. Additionally, capturing more dynamic events, such as sports or moving ground targets [101], [103], necessitates accurate motion prediction, such as player or target movement, which, in turn, relies on coordinated trajectory planning and 3D placement of all UAVs. Furthermore, the trajectory and placement of UAVs must also consider their battery levels, in addition to QoE considerations.

In multi-UAV applications, the individual UAV can collaboratively and cohesively capture videos, which are then synthesized into a panoramic video. However, streaming videos from all UAVs simultaneously poses a significant resource burden. To address this challenge, bandwidth-saving streaming techniques can be employed by leveraging user attention information [104]. Specifically, UAVs whose videos are deemed unnoticed by users can remain idle during transmission. However, we argue that instead of staying idle, these UAVs can contribute to real-time video streaming, thus enhancing communication efficiency and throughput further. For instance, the UAV swarm can collectively form a virtual multiple-input and multiple-output (MIMO) system [105]. Nonetheless, this type of MIMO system exhibits distinct wireless channel characteristics. Considering the unique channel model and the requirements for throughput and latency, thus designing cooperative aerial video streaming for real-time and interactive panoramic videos poses considerable challenges.

Addressing these challenges in cooperative aerial video streaming requires innovative solutions that account for coordination, resource optimization, wireless channel characteristics, throughput, and latency requirements. Meeting these objectives will contribute to the development of robust and efficient systems for real-time and interactive panoramic video streaming.

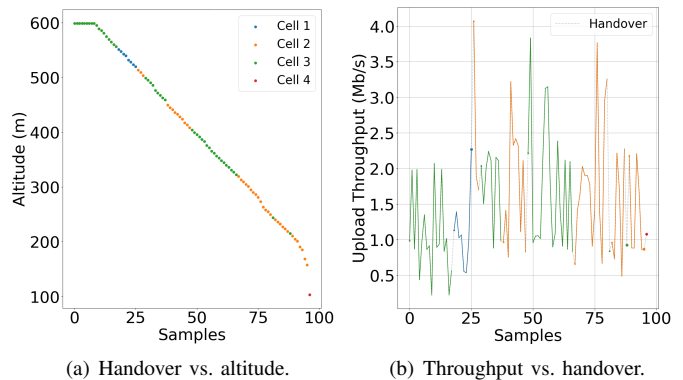


Fig. 6. Handovers and instantaneous throughput performance versus the drone altitude in vertical landing flying conditions. The average throughput values of the cells in green, orange, blue, and red are 14.55 Mbps, 17.19 Mbps, 11.21 Mbps, and 10.79 Mbps, respectively.

### C. QoE-Aware Control and Communication of UAVs

Ensuring high-quality user experience in 360° video streaming systems is primarily affected by stall time resulting from low transmission rates and overall video quality perceived by users [106]. Experiencing a stall time longer than the tolerance level can lead to VR sickness, making it crucial to achieve high data rates and low-latency transmission for enhancing QoE [107]. Addressing these challenges requires leveraging video saliency to predict users' FoV and employing multicast transmission techniques based on users' locations and FoV correlations, as grouping and multicasting can improve network throughput and QoE [108], [109]. Additionally, adapting the encoding bitrate of tiles based on channel quality, available resources, content quality, and inaccurate FoV prediction can further enhance QoE [107].

In the context of VR streaming from aerial users, such as drones, additional challenges arise due to their dynamic topology and limited energy resources [110], [111]. The channel quality and network throughput of aerial users are also influenced by their flight trajectory, necessitating the joint design of QoE-aware resource allocation and drone route selection mechanisms [112], [113]. Moreover, the limited on-board energy availability of drones requires judicious resource allocation strategies [114]. Furthermore, in a multi-UAV-based streaming system for 360° videos [56], additional challenges arise in terms of resource allocation among the UAVs. Each UAV can independently adjust its encoding bitrate and position [115], while simultaneously competing for resources with other UAVs in the swarm. Given these significant challenges, designing a UAV-based 360° streaming system necessitates a thorough study of joint communication and control design for these systems.

In critical missions involving the teleoperation of UAVs, such as fire disaster monitoring [71] and suspicious vehicle tracking [116], the quality of service relies on the interplay between control command delivery and video data transmission. The latency experienced in one link can impact the latency budget in the other link. Moreover, unreliable control command communication can influence the UAV's reaction and view angle, resulting in undesired information for

the remote operator. Therefore, the entanglement and mutual influence between control command delivery and real-time UAVs video transmission require dedicated consideration in the design process.

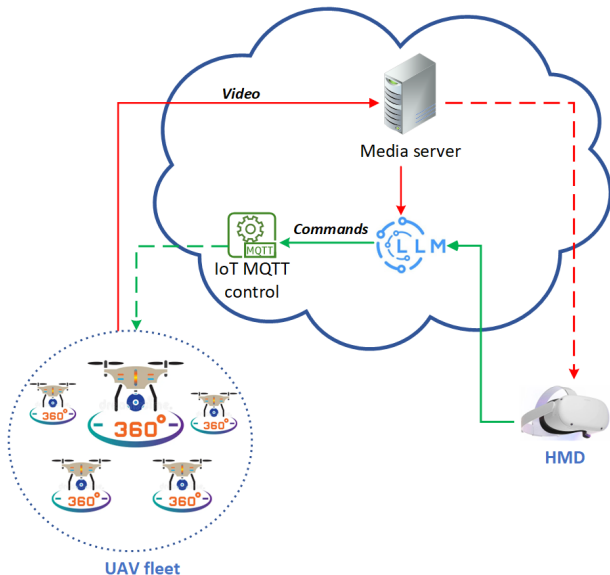


Fig. 7. Use case scenario for LLMs control commands for UAV with 360° camera.

#### D. Tailored Design of UAV Communication for Video Streaming

The design and optimization of UAV wireless communication systems for real-time video streaming pose several open challenges. While theoretical solutions and algorithms have been proposed, many of them focus on incorporating specific characteristics of video streaming and air-to-ground channels, as well as addressing communication requirements. However, in practical testbed implementations, the existing protocols are often used without tailored optimization for video streaming, resulting in limited performance evaluation in real-world scenarios. To enable more immersive services in the context of 6G networks, it is essential to dedicate effort towards implementing wireless protocols specifically tailored to the demands of video streaming. Currently, the wireless system primarily considers factors such as video capture rate or bitrate, neglecting other important aspects.

One approach to achieve video streaming-tailored wireless systems is to incorporate additional characteristics of video encoding in the design. For example, considering the correlation among frames in video content can enhance video encoding efficiency. Additionally, adopting a semantic communication approach, as explored in [117], where the focus is on effectively conveying the semantic meaning of information rather than solely delivering digital bits, shows promise in realizing UAV communication systems tailored for video streaming. Addressing these challenges and exploring novel techniques that take into account video content correlation, semantic communication, and other relevant factors will be crucial in developing efficient and optimized wireless systems for UAV video streaming applications.

#### E. LLM for Immersive Video Streaming

The rapid advancement in natural language processing (NLP) has paved the way for the development of LLMs like BERT [118], GPT-3/GPT-4, and FALCON. These versatile models push the state-of-the-art on many down-stream tasks, finding applications in various domains, including conversation, medicine, telecommunications [119], and robotics [120].

In the context of streaming 360-degree video from one or multiple UAVs, exploring these LLMs can greatly enhance performance. For example, end users can provide task prompts to the LLM along with descriptions of the environment captured by the 360-degree camera. The LLM can then generate commands for the UAVs to carry out the tasks successfully while minimizing their energy consumption and avoiding obstacles. In particular, the description of the surrounding environment from the 360-degree camera can be performed by the end user or automatically by exploiting vision-language models, such as SimVLM [121], Flamingo [122], or BLIP-2 [123].

### VIII. CONCLUSION

In this paper, we have investigated omnidirectional video streaming over UAVs, focusing on the benefits and challenges associated with live 360-degree video streaming. By enabling immersive viewing with up to 6DoF, this technology enhances the QoE for various applications such as surveillance, autonomous driving, healthcare, and education. However, 360-degree video streaming poses challenges in terms of high bandwidth and computing requirements, while the UAV wireless channel exhibits interference and instability, leading to significant bandwidth variations. To overcome these challenges, we first reviewed the key components of 360-degree video streaming over wireless channels and highlighted the technology used to achieve low-latency end-to-end streaming. Additionally, we introduced a new dataset consisting of ten 360-degree videos captured by UAV in various flying conditions, enabling us to evaluate the coding efficiency and complexity of different Software (SW) and Hardware (HW) video encoders. Through our experiments, we found that only HW AVC/H.264 and HEVC/H.265 encoders achieved real-time encoding, making them suitable for UAV with limited computing and energy resources. Furthermore, the SW AV1 encoder demonstrated the best tradeoff between coding performance and complexity and thus be utilized for efficient video transcoding on more powerful devices in the cloud. Moreover, we presented a real testbed of 360-degree video streaming over a drone with 5G communication, illustrating the significant fluctuations in the wireless channel due to interference and multiple handovers. Finally, we discussed open challenges and proposed future research directions to enhance the key performance metrics of live immersive video streaming over UAVs.

Overall, this paper provides valuable insights into the field of omnidirectional video streaming over UAVs and contributes to the understanding of how to improve the QoE in this context. The findings and recommendations presented here pave the way for further advancements and innovations in the

area of live immersive video streaming over UAVs, ultimately benefiting a wide range of applications and industries.

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