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Towards Efficient Bandwidth Management in Live Video Streaming using Redundancy Exploitation

[1]Azegba Okechukwu Levi, [2]Eze-Udu Emmanuel, [3]Aniji Ifesinachi, [4]Ugwoke Sylvester Ikedichi, [5]Ekeh Lawrence Kelechi, [6]Okereke Chidiebere Celestine
[1,2,3&5]Alex-Ekwueme Federal University, Ndufu Alike, Ebonyi State.
[4]National Space Research and Development Agency
[6]Michael Okpara University of Agriculture, Umudike.

ABSTRACT
The rapid growth of the Internet and increasing demand for multimedia services have significantly accelerated the adoption of video streaming applications. Despite these advancements, efficient bandwidth utilization remains a major challenge due to the best-effort nature of Internet services. One of the primary factors contributing to inefficient bandwidth usage is data redundancy within video streams. Effective identification and elimination of these redundancies can significantly improve bandwidth efficiency and enhance the Quality of Service (QoS) of live video streaming systems. This paper examines the major forms of redundancy present in digital video, including spatial, temporal, spatio-temporal, perceptual, and statistical redundancies. It further discusses how these redundancies can be exploited through video compression techniques to reduce transmission overhead and improve streaming performance. By minimizing redundant information, factors such as transmission delay, frame loss, and video quality degradation can be significantly reduced, thereby ensuring optimal bandwidth utilization even under constrained network conditions.

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INTRODUCTION

A video is a sequence of images, commonly referred to as frames, displayed at a sufficiently high rate to create the illusion of continuous motion (Apostolopoulos et al., 2002; Mahini et al., 2017; Adedokun et al., 2019; Schodl et al., 2023). Traditionally, video content was captured, processed, and transmitted in analog form. However, advancements in integrated circuit technology and digital signal processing have facilitated the transition from analog to digital video systems, thereby revolutionizing the storage, processing, compression, and transmission of multimedia content (Apostolopoulos et al., 2002; Zhou & Li 2024). Digital video has become the dominant medium for information dissemination due to its flexibility, scalability, and compatibility with modern communication networks.

The emergence of the Internet and the rapid expansion of network infrastructures have significantly contributed to the growth of video-based applications (Daniel et al., 20221). During the early 2000s, improvements in network bandwidth, coupled with advances in video compression algorithms and increased computational power, made video streaming a practical reality (Zou et al., 2015). Consequently, commercial multimedia applications such as QuickTime, ActiveMovie, and RealPlayer became widely adopted, transforming the way multimedia content is delivered and consumed over the Internet (Zou et al., 2015). Today, video streaming represents one of the largest contributors to Internet traffic, driven by the increasing popularity of online entertainment, social media platforms, e-learning systems, telemedicine, remote collaboration, and video conferencing services.

Corresponding author: Azegba Okechukwu Levi
okechukwu.azegbe@funai.edu.ng
Alex-Ekwueme Federal University, Ndufu Alike, Ebonyi State.

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Streaming refers to the continuous delivery of multimedia content, such as audio and video, over a communication network in a manner that allows playback while the content is still being transmitted. Streaming can be categorized into stored video streaming and live video streaming. Stored video streaming involves the transmission of pre-recorded content, whereas live video streaming involves the real-time capture, encoding, transmission, and playback of multimedia content as events occur (Viola et al., 2023). The real-time nature of live video streaming imposes stringent requirements on network resources and system performance, making it one of the most challenging multimedia applications to support effectively.

The demand for live video streaming services has grown tremendously in recent years. Applications such as online lectures, live sports broadcasts, virtual meetings, surveillance systems, telemedicine, and social networking platforms increasingly rely on real-time video delivery to enhance user engagement and communication. According to Azhar et al. (2016), more than 64% of Internet traffic in 2014 was attributed to multimedia streaming services, a figure that has continued to increase with the proliferation of mobile devices and broadband Internet access. This rapid growth has intensified the need for efficient bandwidth utilization and improved QoS mechanisms.

Despite its widespread adoption, live video streaming remains highly demanding in terms of storage, computational power, and network bandwidth. A digital video consists of a large number of frames transmitted sequentially, with each frame containing thousands or millions of pixels. Consequently, uncompressed video data requires substantial storage space and transmission capacity. The large volume of data associated with video content poses significant challenges, particularly in bandwidth-constrained environments where network resources are limited (Wang et al., 2013; Kumar & Kumar, 2016). Furthermore, the buffering time experienced by end-users is largely dependent on the available network bandwidth and the efficiency of the video transmission process (Apostolopoulos et al., 2002).

Network congestion remains one of the primary causes of degraded streaming performance. Congestion may arise due to heavy network traffic, limited bandwidth availability, packet losses, transmission delays, and fluctuating network conditions. These factors adversely affect the QoS by causing interruptions, frame losses, increased latency, reduced video resolution, and poor user experience (Kumar & Kumar, 2016). As a result, researchers and industry practitioners continue to explore innovative techniques for reducing the amount of data transmitted during video streaming while maintaining acceptable visual quality.

Video compression has emerged as one of the most effective solutions for reducing bandwidth consumption and improving transmission efficiency. Compression techniques aim to eliminate unnecessary or redundant information within video sequences, thereby reducing the amount of data that must be stored or transmitted across the network. Over the years, several compression algorithms and coding standards have been developed to improve bandwidth utilization while minimizing transmission costs and preserving video quality (Azhar et al., 2016). The effectiveness of these techniques largely depends on their ability to identify and exploit various forms of redundancy present in video data.

One notable approach is the frame indexing technique proposed by Kumar and Kumar (2016), which improves compression efficiency by transmitting a reference frame, a difference buffer, and indexing information required for reconstructing subsequent frames. Although the technique demonstrated improved bandwidth utilization and reduced transmission costs, the generated difference buffer still contained significant pixel redundancies, particularly spatial redundancies, thereby limiting its overall efficiency. To further improve compression performance, Canel et al. (2018) proposed a deep neural network-based approach for identifying and selecting relevant frames in streaming video. The technique successfully

Corresponding author: Azegba Okechukwu Levi
okechukwu.azegbe@funai.edu.ng
Alex-Ekwueme Federal University, Ndufu Alike, Ebonyi State.

reduced the number of transmitted frames while maintaining important visual information. However, the method introduces additional memory overhead and processing delays when large buffers are employed.

Subsequently, Adedokun et al. (2019) proposed a spatio-temporal frame indexing algorithm that simultaneously exploits both spatial and temporal redundancies present in video streams. Experimental results demonstrated improved QoS and bandwidth utilization compared with earlier frame indexing approaches. Nevertheless, the study primarily focused on low-motion video streams and did not consider other forms of redundancy such as perceptual and statistical redundancies, which can also contribute significantly to compression efficiency.

It is evident from existing literature that redundancy remains one of the major bottlenecks affecting efficient video transmission. Since substantial similarities exist within and between video frames, identifying and exploiting these redundancies can significantly reduce the amount of information that needs to be encoded and transmitted. Effective redundancy reduction not only improves compression efficiency but also enhances bandwidth utilization, reduces transmission delays, minimizes packet losses, and improves the overall QoS experienced by users.

This paper therefore presents a comprehensive review of the various forms of redundancies that exist in digital video, including spatial, temporal, spatio-temporal, perceptual, and statistical redundancies. The study discusses how these redundancies can be exploited to achieve higher compression efficiency and optimal bandwidth utilization in live video streaming systems. The remainder of the paper is organized as follows: Section II discusses the significance of video compression, Section III presents the various forms of redundancies in digital video, Section IV discusses challenges and future research directions, and Section V concludes the paper.

Significance of Video Compression

The increasing demand for multimedia applications such as live video streaming, video conferencing, online learning, telemedicine, surveillance systems, and Internet television has resulted in a substantial growth in digital video traffic across communication networks. Digital video inherently requires a large amount of storage space and transmission bandwidth due to the enormous volume of information contained in video frames. Consequently, efficient video compression has become an indispensable component of modern multimedia communication systems.

A digital video is composed of a sequence of frames displayed in rapid succession to create the perception of motion. Each frame consists of a collection of pixels, with every pixel represented by a certain number of bits depending on the color model and image quality. As a result, raw or uncompressed video data requires enormous storage and transmission resources. For example, a standard-definition video with a resolution of 720 × 480 pixels, operating at 27 frames per second (fps) and represented using the RGB color model (3 bytes per pixel), requires approximately:

Memory Requirement per Second

$720 \times 480 \times 27 \times 3 = 27{,}993{,}600$ bytes ≈ 28 MB

Thus, storing one hour of such uncompressed video would require approximately 112 GB of storage space. Furthermore, transmitting this video in real time would require a bandwidth of approximately:

$28 \times 8 = 224$ Mbps

Such bandwidth requirements are impractical for many communication networks, especially wireless and mobile networks where bandwidth resources are limited and network conditions are highly dynamic. Therefore, transmitting uncompressed video is generally infeasible due to excessive storage requirements, high transmission costs, and significant computational demands.

Besides storage and transmission concerns, uncompressed video also increases the complexity and cost of hardware systems used for video processing. Devices responsible for capturing, encoding, transmitting, storing, and

Corresponding author: Azegba Okechukwu Levi
okechukwu.azegbe@funai.edu.ng
Alex-Ekwueme Federal University, Ndufu Alike, Ebonyi State.

displaying video must possess higher processing capabilities and larger memory capacities to handle raw video streams efficiently. Consequently, the deployment and maintenance costs of multimedia systems become significantly higher.

Video compression addresses these challenges by reducing the amount of data required to represent video information without substantially degrading perceived visual quality. Compression techniques exploit the redundancies and irrelevancies present in video sequences to eliminate unnecessary information before transmission or storage. By reducing the size of video data, compression enables efficient utilization of network bandwidth, lowers storage requirements, decreases transmission delays, and improves the overall QoS experienced by end users (Lee & Kalva, 2011).

The importance of video compression becomes even more evident in live video streaming applications, where content is captured, encoded, transmitted, and displayed in real time. Unlike stored video applications, live streaming systems operate under strict timing constraints and cannot tolerate excessive delays. In such environments, efficient compression mechanisms are essential for ensuring smooth playback, minimizing buffering delays, reducing packet losses, and maintaining acceptable video quality under varying network conditions (Apostolopoulos et al., 2002).

Furthermore, video compression contributes significantly to improving bandwidth utilization. Since bandwidth is a finite and often costly resource, reducing the amount of data transmitted over the network enables more users to be served simultaneously without causing network congestion. Efficient compression techniques therefore increase network scalability while maintaining service quality. This is particularly important in applications such as video conferencing, distance learning, live sports broadcasting, and social media streaming, where large numbers of users may access content concurrently.

Over the years, researchers have developed numerous video coding standards and compression techniques aimed at improving compression efficiency. Modern video coding standards such as H.264/AVC, H.265/HEVC, and AV1 achieve substantial reductions in bit rate by exploiting various forms of redundancy present in video sequences. These redundancies include spatial, temporal, perceptual, and statistical redundancies, each of which contributes to reducing the amount of information that must be encoded and transmitted (Lee & Kalva, 2011; Ponlatha & Sabeenian, 2013).

In addition to bandwidth savings, video compression improves transmission reliability and network performance. Smaller compressed video streams experience lower transmission delays and are less susceptible to packet loss and network congestion. Consequently, users receive higher-quality video content with fewer interruptions and reduced buffering times. This directly enhances the Quality of Experience (QoE), which is a critical metric for evaluating user satisfaction in multimedia applications (Duanmu et al., 2017).

Recent studies have also demonstrated that advanced compression techniques can significantly improve bandwidth utilization in live video streaming systems. Kumar and Kumar (2016) proposed a frame indexing method that reduces the amount of transmitted data by transmitting reference frames and differential information. Similarly, Adedokun et al. (2019) introduced a spatio-temporal frame indexing algorithm that exploits both spatial and temporal redundancies to improve QoS and bandwidth efficiency in low-motion live video streaming applications. These studies further emphasize the critical role of redundancy exploitation in achieving efficient video transmission.

Therefore, video compression serves as the foundation of modern video communication systems. By reducing storage requirements, minimizing bandwidth consumption, lowering transmission costs, mitigating network congestion, and improving QoS, compression technologies make large-scale video streaming applications practical and economically viable. The effectiveness of these technologies largely depends on their ability to identify and exploit the

Corresponding author: Azegba Okechukwu Levi
okechukwu.azegbe@funai.edu.ng
Alex-Ekwueme Federal University, Ndufu Alike, Ebonyi State.

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various forms of redundancy inherent in digital video, which are discussed in the subsequent section. The efficiency of live video streaming systems depends largely on the ability of compression algorithms to identify and eliminate redundant information contained within video streams. By exploiting various forms of video redundancies, the amount of data required for transmission can be significantly reduced, leading to improved bandwidth utilization and enhanced streaming performance. Figure 1 presents the conceptual framework illustrating the relationship between redundancy exploitation, video compression, bandwidth optimization, and QoS improvement in live video streaming systems.

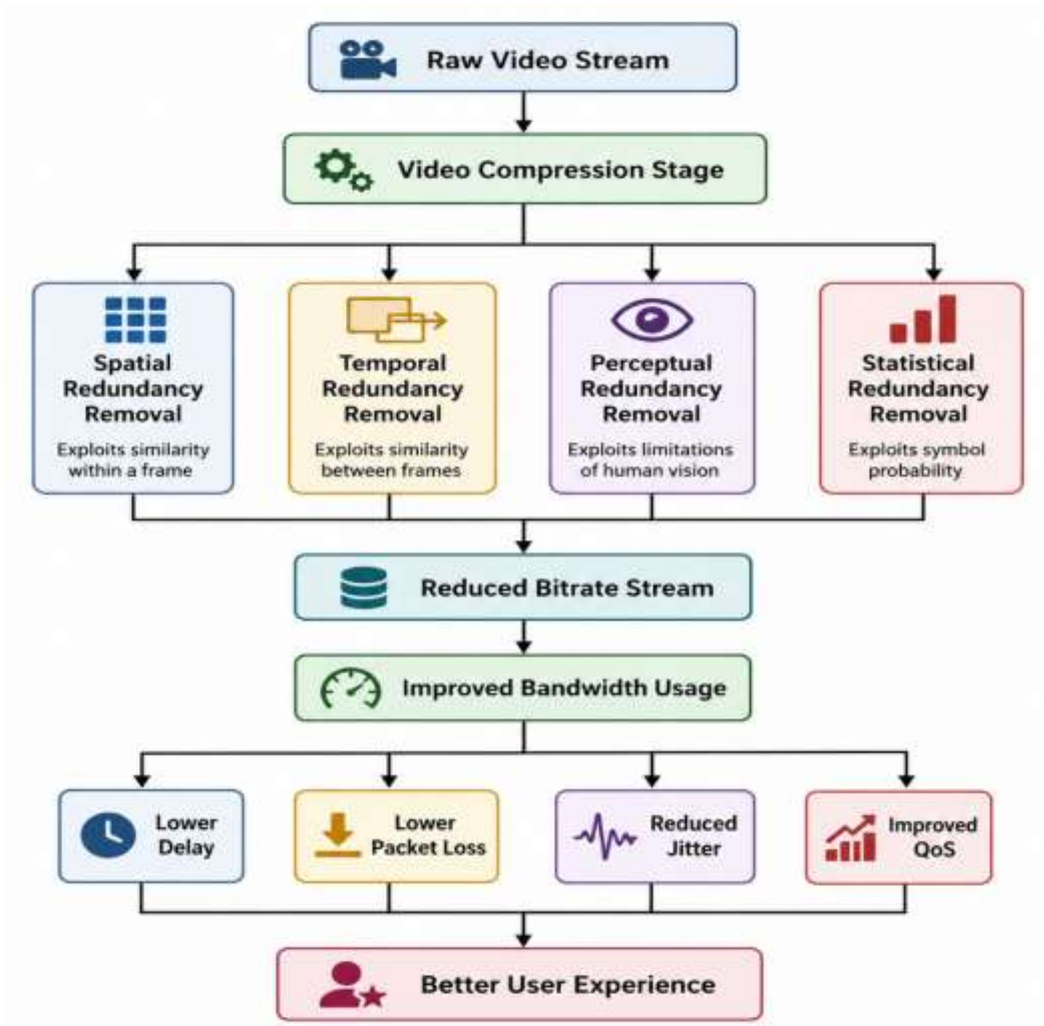

Figure 1: Conceptual Framework for Bandwidth Optimization through Redundancy Exploitation

As illustrated in Figure 1, the video compression process exploits spatial, temporal, perceptual, and statistical redundancies to reduce the bitrate of transmitted video streams. The resulting reduction in data volume leads to more efficient utilization of available bandwidth, which in turn contributes to lower transmission delays, reduced packet losses, minimized jitter, and

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okechukwu.azegbe@funai.edu.ng
Alex-Ekwueme Federal University, Ndufu Alike, Ebonyi State.

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improved QoS. Collectively, these improvements enhance the overall QoE perceived by end-users, highlighting the critical role of redundancy-aware compression techniques in modern video streaming applications.

Types of Video Redundancies

The effectiveness of video compression techniques largely depends on their ability to identify and eliminate redundant information contained within a video sequence. Redundancy refers to the presence of information that is either repeated, predictable, or insignificant to human perception. Since a video consists of a sequence of highly correlated images, substantial redundancy exists both within individual frames and across consecutive frames. By exploiting these redundancies, video coding systems can significantly reduce the amount of data required for storage and transmission without noticeably affecting visual quality. Various forms of redundancies exist in digital video, and each contributes differently to the overall compression process. The major categories of video redundancies include spatial redundancy, temporal redundancy, 44-temporal redundancy, perceptual redundancy, and statistical redundancy.

Spatial Redundancy

Spatial redundancy, also referred to as intra-frame redundancy, exists within a single video frame. It arises because neighboring pixels within an image often possess similar intensity values, colors, or texture characteristics. In most natural images, adjacent pixels are highly correlated, particularly in smooth regions where changes in brightness and color occur gradually (Lee & Kalva, 2011).

For example, in an image containing a clear blue sky, thousands of neighboring pixels may have nearly identical color values. Storing each pixel value independently would therefore result in considerable duplication of information. Instead, compression algorithms exploit this similarity by representing groups of neighboring pixels using fewer bits.

Modern video coding standards utilize various techniques to exploit spatial redundancy. These techniques include predictive coding, transform coding, and block-based compression methods. In predictive coding, the value of a pixel or block is estimated using information from neighboring pixels, and only the prediction error is encoded. Similarly, transform coding techniques such as the Discrete Cosine Transform (DCT) concentrate image energy into a small number of coefficients, enabling efficient compression.

The exploitation of spatial redundancy significantly reduces the amount of data that must be encoded and transmitted. This reduction directly contributes to lower bandwidth consumption and improved transmission efficiency. However, the effectiveness of spatial redundancy reduction depends largely on image characteristics. Images containing complex textures, sharp edges, or significant noise exhibit lower spatial correlation and therefore provide fewer opportunities for spatial compression (Ponlatha & Sabeenian, 2013). Despite its limitations, spatial redundancy remains one of the fundamental sources of compression gain in modern image and video coding systems.

Temporal Redundancy

Temporal redundancy, also known as inter-frame redundancy, refers to the similarity that exists between consecutive video frames (Kumar & Kumar, 2016; Adedokun et al., 2019). Since video is essentially a sequence of images captured at short time intervals, successive frames often contain very little change, particularly in low-motion scenes.

For instance, during a video conference or an online lecture, the background may remain unchanged for several seconds while only minor movements occur. In such cases, transmitting every frame in its entirety would result in substantial duplication of information. Temporal redundancy exploits these similarities by encoding only the differences between successive frames rather than transmitting complete frames repeatedly.

Motion estimation and motion compensation are among the most widely used

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okechukwu.azegbe@funai.edu.ng
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techniques for exploiting temporal redundancy. Motion estimation identifies the movement of objects between frames, while motion compensation predicts the current frame based on previously transmitted frames. Only the motion information and prediction errors are subsequently encoded and transmitted.

The simplest form of temporal compression is frame differencing, where the difference between two consecutive frames is calculated and encoded. Since the resulting difference frame often contains much less information than the original frame, significant reductions in bit rate can be achieved (Lee & Kalva, 2011). Temporal redundancy typically provides the largest compression gains in low-motion video sequences because adjacent frames exhibit strong correlation. However, its effectiveness decreases in high-motion videos where rapid object movement causes substantial differences between consecutive frames. Similarly, abrupt scene changes can significantly reduce temporal correlation and limit compression efficiency.

Kumar and Kumar (2016) utilized temporal redundancy in their frame indexing approach to improve bandwidth utilization in live video streaming. Although their method achieved considerable data reduction, residual spatial redundancies remained within the generated difference buffers, preventing optimal compression performance.

Spatio-Temporal Redundancy

Spatio-temporal redundancy combines the advantages of both spatial and temporal redundancy exploitation. This form of redundancy recognizes that similarities exist not only within individual frames but also across multiple frames in a video sequence. By jointly exploiting these correlations, higher compression efficiency can be achieved than when either technique is used independently.

Traditional video compression approaches often focus primarily on either spatial or temporal redundancy. However, relying solely on one form of redundancy may not fully capture all the available compression opportunities. For example, while temporal prediction may effectively remove inter-frame similarities, residual redundancies often remain within the resulting prediction errors. These residual redundancies can subsequently be reduced through spatial compression techniques.

To address this challenge, Adedokun et al. (2019) proposed a spatio-temporal frame indexing algorithm that simultaneously exploits both spatial and temporal correlations in live video streams. The approach demonstrated improved QoS and enhanced bandwidth utilization when compared with purely temporal frame indexing methods.

The primary advantage of spatio-temporal redundancy exploitation is its ability to achieve higher compression ratios by reducing both intra-frame and inter-frame redundancies simultaneously. Consequently, less data must be transmitted over the network, resulting in lower bandwidth consumption and improved streaming performance. However, the implementation of spatio-temporal compression techniques often increases computational complexity. Additional processing is required to analyze both spatial and temporal relationships, which may increase encoding time and memory requirements. Furthermore, the frame reconstruction process becomes more complex due to the additional indexing information needed for successful decoding (Adedokun et al., 2019). Despite these challenges, spatio-temporal redundancy remains one of the most promising approaches for achieving optimal bandwidth utilization in live video streaming systems.

Perceptual Redundancy

Perceptual redundancy arises from the limitations of the Human Visual System (HVS). The human eye is not equally sensitive to all visual information present in an image or video sequence. Certain details, color variations, and high-frequency components can be removed or approximated without causing noticeable degradation in perceived image quality (Lee & Kalva, 2011).

This characteristic provides a valuable opportunity for compression. Information that is

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okechukwu.azegbe@funai.edu.ng
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unlikely to be perceived by viewers can be discarded during the encoding process, thereby reducing the amount of data that must be transmitted. Unlike spatial and temporal redundancy, which rely on statistical similarities, perceptual redundancy exploits the physiological characteristics of human vision.

One of the most common examples of perceptual redundancy exploitation is color subsampling. The Human Visual System is generally more sensitive to brightness information than to color information. Consequently, many video coding systems convert images from the RGB color space to the YCbCr color space, where Y represents luminance (brightness) and Cb and Cr represent chrominance (color components). Because humans are less sensitive to chrominance details, the color components can be sampled at lower resolutions without significantly affecting perceived visual quality. This technique substantially reduces data size while maintaining an acceptable viewing experience. Modern video compression standards extensively utilize perceptual redundancy through quantization, chroma subsampling, and perceptually optimized encoding algorithms. These techniques enable significant reductions in bit rate while preserving subjective image quality.

Statistical Redundancy

Statistical redundancy occurs because certain symbols, pixel values, transform coefficients, or motion vectors appear more frequently than others in compressed video data. When all symbols are represented using fixed-length codes, storage and transmission resources are often wasted because frequently occurring values occupy the same number of bits as infrequently occurring values (Lee & Kalva, 2011). For example, a fixed-length coding scheme may allocate 16 bits to represent every value regardless of its probability of occurrence. In practice, however, some values appear much more frequently than others. Assigning identical code lengths to all values therefore results in inefficient data representation.

To address this issue, entropy coding techniques exploit statistical redundancy by assigning shorter code words to frequently occurring symbols and longer code words to less frequent symbols. Common entropy coding methods include Huffman Coding, Arithmetic Coding, Context-Adaptive Variable Length Coding (CAVLC), and Context-Adaptive Binary Arithmetic Coding (CABAC). By reducing the average number of bits required to represent encoded information, statistical redundancy exploitation provides additional compression gains beyond those achieved through spatial and temporal techniques. Consequently, entropy coding serves as the final stage in many modern video compression systems.

According to Duanmu et al. (2017) and Parodkar and Bade (2015), variable-length coding techniques significantly improve compression efficiency and contribute to more effective bandwidth utilization in multimedia communication systems. Although statistical redundancy typically provides smaller compression gains compared to spatial and temporal redundancy, its contribution remains essential for achieving high overall compression ratios. The various forms of redundancies present in digital video contribute differently to the overall compression process. Each redundancy type exploits a specific characteristic of video data, enabling the reduction of storage requirements and transmission bandwidth while maintaining acceptable visual quality. Understanding the strengths, limitations and associated compression techniques of these redundancies is essential for designing efficient video streaming systems. Table 1 provides a summary of the major video redundancies and their contributions to video compression and bandwidth optimization.

Table 1: Summary of Video Redundancies and Their Impact on Compression

Corresponding author: Azegba Okechukwu Levi
okechukwu.azegbe@funai.edu.ng
Alex-Ekwueme Federal University, Ndufu Alike, Ebonyi State.

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Redundancy Type	Description	Compression Technique	Advantages	Limitations
Spatial Redundancy	Similarity among neighboring pixels within a frame	Intra-frame prediction, DCT, Transform Coding	Reduces frame size significantly	Less effective in highly textured images
Temporal Redundancy	Similarity between consecutive frames	Motion Estimation, Motion Compensation, Frame Differencing	Provides major compression gains in low-motion videos	Poor performance in high-motion scenes
Spatio-Temporal Redundancy	Combination of spatial & temporal similarities	Frame Indexing, Hybrid Compression Methods	Higher compression ratio and bandwidth savings	Increased computational complexity
Perceptual Redundancy	Information not easily perceived by human vision	Chroma Subsampling, Quantization	Significant bitrate reduction with minimal quality loss	Excessive reduction may affect visual quality
Statistical Redundancy	Unequal probability of occurrence of symbols	Huffman Coding, Arithmetic Coding, CABAC	Improves coding efficiency	Smaller gains compared to spatial and temporal redundancy

As shown in Table 1, modern video compression systems achieve high compression efficiency through the combined exploitation of multiple forms of redundancy. While temporal redundancy often provides the greatest bandwidth savings in low-motion video sequences, spatial, perceptual, and statistical redundancies also play significant roles in reducing the amount of information that must be transmitted. Consequently, contemporary video coding standards such as H.264/AVC, H.265/HEVC, and AV1 integrate several redundancy reduction techniques within a unified compression framework.

The effective utilization of these redundancies directly contributes to improved bandwidth efficiency, enhanced Quality QoS, and better user experience in live video streaming applications. The performance of live video streaming systems is commonly evaluated using several QoS metrics that directly influence user satisfaction. Efficient bandwidth utilization serves as a key factor in determining the effectiveness of these performance indicators. Figure 2 illustrates the relationship between bandwidth utilization, video compression, QoS performance metrics, and the resulting QoE perceived by users.

Corresponding author: Azegba Okechukwu Levi
okechukwu.azegbe@funai.edu.ng
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Figure 2: Relationship between bandwidth optimization, QoS parameters, and QoE in live video streaming.

Figure 2 demonstrates that effective video compression contributes significantly to improved bandwidth utilization, which subsequently influences critical QoS parameters such as delay, jitter, packet loss, and video quality. Improvements in these metrics directly enhance the Quality of Experience experienced by end-users. Therefore, achieving optimal bandwidth utilization through efficient compression and redundancy exploitation remains essential for delivering reliable, high-quality, and scalable live video streaming services across diverse network environments.

Quality of Service Requirements in Live Video Streaming

QoS refers to the capability of a communication network to provide predictable and satisfactory service performance to users. In live video streaming applications, QoS is particularly important because multimedia content is highly sensitive to network impairments such as delay, packet loss, bandwidth fluctuations, and jitter. Unlike traditional data applications where delayed delivery may be acceptable, live video streaming requires real-time delivery of information to ensure seamless viewing experiences. Consequently, maintaining a high level of QoS remains one of the primary objectives of modern video streaming systems (Apostolopoulos et al., 2002). The quality perceived by end-users depends on several network and application-level parameters. These parameters collectively determine whether a video stream can be delivered smoothly, efficiently, and with acceptable visual quality.

Bandwidth Availability

Bandwidth represents the maximum amount of data that can be transmitted through a communication channel within a specified period. It is one of the most critical resources required for video streaming applications. Higher video resolutions, frame rates, and color depths require larger bandwidth allocations for successful transmission. Insufficient bandwidth often results in video degradation, increased buffering time, reduced frame rates, and lower image quality. Modern streaming platforms employ adaptive bitrate streaming techniques to dynamically adjust video quality according to available bandwidth. However, efficient video compression remains essential for minimizing bandwidth consumption and ensuring uninterrupted playback (Azhar et al., 2016). Effective exploitation of video redundancies directly contributes to bandwidth conservation by reducing the amount of information that must be transmitted over the network. Consequently, more users can be served simultaneously without significantly affecting service quality.

End-to-End Delay

Corresponding author: Azegba Okechukwu Levi
okechukwu.azegbe@funai.edu.ng
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End-to-end delay refers to the total time required for a video packet to travel from the source to the destination. In live video streaming, delay consists of encoding delay, processing delay, transmission delay, propagation delay, and decoding delay. Low latency is essential for applications such as video conferencing, online gaming, remote surgery, and live event broadcasting. Excessive delays can disrupt communication, reduce interactivity, and negatively affect user experience. According to Apostolopoulos et al. (2002), real-time multimedia applications impose stringent delay constraints that require efficient encoding and transmission mechanisms. Video compression techniques contribute to delay reduction by decreasing the amount of data transmitted over the network, thereby reducing transmission and buffering times.

Packet Loss

Packet loss occurs when transmitted packets fail to reach their intended destination. Losses may result from network congestion, transmission errors, hardware failures, or wireless interference. Video streaming applications are highly sensitive to packet losses because missing packets can lead to frame corruption, visual artifacts, freezing, and degradation of video quality. The effects of packet loss are particularly severe in compressed video streams because the loss of a reference frame may affect the decoding of subsequent frames. Reducing the bitrate through effective redundancy elimination can lower network congestion and consequently reduce packet loss rates. Therefore, efficient video compression indirectly enhances QoS by improving transmission reliability.

Jitter

Jitter refers to variations in packet arrival times at the receiver. Ideally, packets should arrive at regular intervals; however, network congestion and route variations often cause irregular delivery patterns. High jitter can result in playback interruptions, synchronization problems, and increased buffering requirements. To compensate for jitter, streaming systems utilize playback buffers, although excessive buffering introduces additional delays. By reducing data transmission requirements, efficient compression helps minimize congestion-related jitter and improves stream stability.

Video Quality

Video quality represents the visual fidelity of the received video relative to the original content. It is one of the most important indicators of user satisfaction. Video quality can be evaluated objectively using metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Video Quality Metrics (VQM). Subjective evaluations based on user perception, often referred to as Quality of Experience (QoE), are also commonly employed (Duanmu et al., 2017). Although compression reduces data size, excessive compression may introduce visual distortions. Therefore, an effective video streaming system must achieve an optimal balance between compression efficiency and visual quality.

Reliability and Scalability

Modern video streaming platforms often serve thousands or even millions of concurrent users. Consequently, scalability and reliability are essential QoS requirements. Efficient utilization of available bandwidth enables streaming servers and networks to support larger user populations without excessive resource consumption. Compression techniques that effectively exploit video redundancies contribute significantly to system scalability by reducing bandwidth demand while maintaining acceptable service quality.

Overall, QoS requirements in live video streaming are closely linked to efficient bandwidth utilization. Improvements in compression efficiency and redundancy exploitation directly enhance bandwidth availability, reduce delay and packet loss, improve video quality, and ultimately increase user satisfaction.

Challenges and Future Directions in Bandwidth Optimization

Despite significant advances in video compression and streaming technologies,

Corresponding author: Azegba Okechukwu Levi
okechukwu.azegbe@funai.edu.ng
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achieving optimal bandwidth utilization in live video streaming remains a challenging research problem. The rapid growth of multimedia traffic, increasing user expectations, and emergence of high-definition video formats continue to place enormous demands on communication networks. Consequently, several technical challenges must be addressed to achieve efficient and sustainable video delivery systems.

High-Motion Video Compression Challenges

Many existing redundancy exploitation techniques perform exceptionally well in low-motion video sequences where consecutive frames exhibit strong temporal correlation. However, their effectiveness decreases considerably in high-motion scenarios such as sports broadcasts, gaming streams, and surveillance videos (Momoh et al., 2020). Rapid object movements and frequent scene changes reduce temporal redundancy, thereby increasing the amount of information that must be encoded and transmitted. Developing compression algorithms capable of efficiently handling high-motion video remains an active area of research (Adedokun et al., 2019). Future research should focus on adaptive redundancy detection mechanisms capable of dynamically adjusting compression strategies according to scene characteristics.

Increasing Demand for High-Resolution Video

The widespread adoption of High Definition (HD), Full HD, 4K, 8K, Virtual Reality (VR), and Augmented Reality (AR) technologies has significantly increased bandwidth requirements. Although modern codecs provide substantial compression gains, the growth in video resolution often offsets these improvements. Future compression techniques must therefore achieve higher compression ratios without introducing noticeable degradation in visual quality. Artificial intelligence and machine learning techniques offer promising opportunities for addressing this challenge through intelligent content-aware compression mechanisms.

Network Heterogeneity

Video streams are increasingly delivered across heterogeneous networks comprising wired, wireless, cellular, satellite, and Internet-of-Things (IoT) infrastructures. These networks exhibit diverse bandwidth capacities, latency characteristics, and reliability levels. Designing adaptive streaming systems capable of maintaining acceptable QoS across heterogeneous environments remains a major challenge. Future streaming architectures should incorporate network-aware compression algorithms capable of dynamically adapting transmission parameters based on real-time network conditions.

Adaptive Bitrate Streaming Optimization

Adaptive Bitrate Streaming (ABR) technologies dynamically adjust video quality according to network conditions. While ABR improves user experience, selecting optimal bitrate levels remains a complex decision-making problem. Frequent bitrate switching may introduce instability and reduce viewer satisfaction. Future research can leverage artificial intelligence techniques to predict network conditions more accurately and optimize bitrate adaptation decisions in real time.

Artificial Intelligence-Based Compression

Artificial Intelligence (AI) and Deep Learning have emerged as promising tools for next-generation video compression. Deep neural networks can learn complex spatial and temporal relationships within video content, enabling more efficient prediction, motion estimation, frame interpolation, and redundancy elimination. AI-assisted video codecs have demonstrated significant potential for achieving higher compression efficiency than conventional methods. Future work should investigate lightweight AI-based compression models that can operate efficiently in real-time streaming environments with limited computational resources.

Edge Computing and Fog-Assisted Streaming

Traditional cloud-based streaming architectures often introduce significant latency

Corresponding author: Azegba Okechukwu Levi
okechukwu.azegbe@funai.edu.ng
Alex-Ekwueme Federal University, Ndufu Alike, Ebonyi State.

and bandwidth overhead due to the centralized nature of processing and storage. Edge computing and fog computing technologies bring computational resources closer to end-users, thereby reducing transmission delays and network congestion (Umoh et al., 2019; Kuchuk, H., & Malokhvii, E. 2024). Video preprocessing, transcoding, caching, and redundancy elimination can be performed at edge nodes before content is transmitted to users. Future streaming systems are expected to integrate edge intelligence with advanced compression techniques to achieve improved bandwidth utilization and reduced latency.

Integration with 5G and Beyond Networks

The deployment of 5G networks has introduced enhanced mobile broadband capabilities, ultra-reliable low-latency communication, and massive machine-type communications (Shobowale et al., 2023). Although 5G significantly improves network performance, the increasing demand for ultra-high-definition streaming continues to challenge available bandwidth resources. Emerging 6G networks are expected to support holographic communications, immersive multimedia experiences, and intelligent networking systems. Future bandwidth optimization techniques must therefore be designed to operate efficiently within next-generation communication infrastructures.

Towards Comprehensive Redundancy Exploitation

Existing studies often focus on exploiting one or two forms of video redundancy. However, achieving truly optimal bandwidth utilization requires a comprehensive framework capable of simultaneously exploiting spatial, temporal, spatio-temporal, perceptual, and statistical redundancies. Such an integrated approach has the potential to significantly improve compression efficiency, reduce transmission costs, minimize network congestion, and enhance Quality of Service. Therefore, future research should focus on developing intelligent hybrid compression frameworks that combine multiple redundancy exploitation techniques within a unified architecture.

The continued evolution of video streaming technologies will depend largely on the ability of researchers and practitioners to address these challenges while maintaining high levels of QoS and user satisfaction.

CONCLUSION

The unprecedented growth of live video streaming applications has intensified the demand for efficient bandwidth utilization and improved QoS(QoS) in modern communication networks. As video traffic continues to dominate Internet usage, the need for effective compression mechanisms capable of reducing transmission overhead while preserving video quality has become increasingly important. Video compression remains one of the most effective approaches for addressing bandwidth limitations, minimizing transmission costs, and enhancing the overall performance of streaming systems.

This paper presented a comprehensive review of the significance of video compression and the various forms of redundancies that exist in digital video streams. Specifically, spatial, temporal, spatio-temporal, perceptual, and statistical redundancies were examined, highlighting their roles in reducing the amount of information that must be encoded, stored, and transmitted. The study further demonstrated that the effective exploitation of these redundancies can substantially improve compression efficiency, reduce network congestion, minimize packet loss, lower transmission delays, and enhance the QoS experienced by end users.

The paper also discussed the critical QoS requirements of live video streaming, including bandwidth availability, latency, packet loss, jitter, video quality, reliability, and scalability. These requirements were shown to be closely linked to efficient bandwidth management and redundancy-aware compression techniques. Furthermore, several emerging challenges affecting bandwidth optimization were identified, including high-motion video compression, increasing demand for ultra-high-definition content, heterogeneous network environments,

Corresponding author: Azegba Okechukwu Levi
okechukwu.azegbe@funai.edu.ng
Alex-Ekwueme Federal University, Ndufu Alike, Ebonyi State.

adaptive bitrate streaming, artificial intelligence-based compression, edge computing integration, and next-generation communication networks.

Based on the reviewed literature, it is evident that no single redundancy exploitation technique can independently achieve optimal bandwidth utilization under all streaming conditions. Therefore, future research should focus on the development of intelligent hybrid compression frameworks capable of simultaneously exploiting spatial, temporal, spatio-temporal, perceptual, and statistical redundancies. Such integrated approaches have the potential to significantly improve compression performance, maximize bandwidth utilization, and ensure sustainable delivery of high-quality video services across diverse network environments.

Ultimately, achieving efficient bandwidth management in live video streaming will require a combination of advanced compression techniques, adaptive network-aware mechanisms, artificial intelligence, and emerging communication technologies. These developments will play a crucial role in supporting the next generation of multimedia applications and ensuring enhanced QoS for an ever-growing population of video streaming users.

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Corresponding author: Azegba Okechukwu Levi
okechukwu.azegbe@funai.edu.ng
Alex-Ekwueme Federal University, Ndufu Alike, Ebonyi State.

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Corresponding author: Azegba Okechukwu Levi
okechukwu.azegbe@funai.edu.ng
Alex-Ekwueme Federal University, Ndufu Alike, Ebonyi State.