Optimizing Video Streaming via Super-Resolution and Task Assignment: A Brief Survey

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Abstract

This brief survey examines computational advances in video streaming leveraging Super-Resolution (SR) to enhance visual quality from lower-bandwidth transmissions and intelligent Task Assignment (TA) to optimize resource utilization across client, edge, and cloud. It highlights key trends in synergistic approaches, focusing on improving Quality of Experience (QoE) and streaming efficiency. The paper also outlines significant challenges and future research directions.

Ⅰ. Introduction

Video consumption now dominates internet traffic, demanding high QoE [1]. Increasing resolution and frame rates strain network resources [2] and client energy consumption. Adaptive bitrate (ABR) [3] streaming mitigates bandwidth limitations, yet struggles with emerging ultrahigh-definition content. SR [1] techniques reconstruct high-resolution frames from lower-resolution inputs, reducing bandwidth needs. Intelligent TA offloads computation to edge servers or utilizes heterogeneous resources. This synergistic approach enhances perceived quality without increasing bandwidth proportionally. Optimizing video streaming requires balancing QoE, bandwidth, and energy efficiency. This paper surveys recent advancements in SR and TA for sustainable high-quality video delivery. These techniques offer promising pathways towards improved streaming experiences and reduced energy consumption.

Ⅱ. Key computational techniques & trends

SR and intelligent TA stand out as pivotal advancements in computational techniques for improving video streaming.

Deep Neural Network (DNN)-based SR is the dominant method for significantly enhancing video quality, surpassing traditional techniques and reconstructing finer details [4, 5]. Recognizing computational demands, lightweight SR models are vital for practical deployment on resource-constrained mobile and edge devices, exemplified by specialized NPU-efficient designs in NAWQ-SR [5] and heterogeneous processor use in MobiSR [12]. A core SR benefit in streaming is improved visual fidelity from lower bitrate streams; this allows perception of high-quality video from reduced data transmission, leading to substantial bandwidth savings and more resilient streaming under poor network conditions [4, 10, 8, 11].

Key trends include content-aware SR, where enhancement techniques dynamically adapt to video-specific visual characteristics and complexity for more efficient upscaling, as demonstrated by DeepStream [10] and NEMO [11]. Another significant development is embedding SR capabilities directly to video codec pipelines. This tighter integration, also explored in DeepStream and NEMO, optimizes performance by leveraging codec information or selectively applying SR to anchor frames. Across these approaches, enhancing “Quality” via SR is a primary objective, as highlighted in Table 1.

Intelligent TA is paramount for managing the computational load of SR and streaming processes. On client devices, strategies leverage heterogeneous processors (CPUs, GPUs, NPUs) for efficient execution by dynamically matching workload characteristics to the most suitable processing architecture. Systems like NAWQ-SR [5], ESHP [6], and MobiSR [12] exemplify on-device “TA” with “Latency” and “Energy” optimizations (Table 1). ESHP, for instance, uses Deep Reinforcement Learning (DRL) for adaptive co-scheduling on heterogeneous hardware.

Edge-assisted architectures offload intensive SR, caching, and ABR decisions to network edges, reducing client burden and serving multiple users [4, 8]. VISCA [8] features edge-based SR and utility-based caching, while Co-Video [4] handles multi-user collaborative edge-end SR. Client-edge-cloud collaboration, seen in Supremo’s [7] mobile-cloud SR, allows dynamic offloading based on system state and network conditions. These assignment strategies aim to minimize client load, reduce “Latency,” and improve “Energy” profiles, as consistently shown in Table 1.

Advanced streaming systems increasingly adopt holistic approaches, jointly optimizing ABR selection, SR quality, and TA. DRL offers a powerful framework for adaptive decision-making in dynamic environments [4, 6, 9]. Edge-centric systems like Co-Video [4] use multi-agent DRL for multi-user QoE optimization, while client-centric/hybrid systems (e.g., NEMO, BONES [9]) focus on on-device efficiency. As Table 1 shows, leading systems concurrently address “Latency,” “Quality,” “Energy,” and “TA”. A crucial trend is dynamic adaptation to fluctuating network, content, and device conditions, ultimately maximizing QoE through intelligent resource orchestration.

Table 1: Comparative Aspects of Video Streaming Research Papers

Aspect	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Latency	x	x	x	x	x	x		x	x
Quality	x	x	x	x	x	x	x	x	x
Energy	x	x	x					x	x
TA	x	x	x	x	x	x		x	x

Ⅲ. Open challenges and future directions

Achieving real-time performance for increasingly complex SR models remains a significant hurdle, demanding a careful balance between enhancement quality and inferencing latency. Ensuring SR models generalize well across diverse video content and scale effectively in dynamic multi-user edge environments presents ongoing research challenges. Improving the energy efficiency of sophisticated SR algorithms is paramount, especially for battery-constrained mobile devices [5, 11]. The development of industry standards for SR-enhanced video streaming is crucial for broader adoption and interoperability. Future work will involve integrating SR with emerging video formats like volumetric [1] and 360° video [1, 4, 9]. Further research into lightweight, adaptive SR architectures and more sophisticated artificial intelligence (AI)-driven resource management is essential. Exploring hardware-software co-design for SR acceleration on specialized processors offers a promising avenue. Additionally, ensuring robust and secure SR processing in distributed environments will gain importance maintaining operational integrity and user trust. Addressing these challenges will pave the way for more immersive and efficient video streaming experiences. The ultimate aim is to make high-quality, low-latency, and energy-efficient streaming universally accessible.

Ⅳ. Conclusion

SR and intelligent TA are crucial for balancing video streaming QoE, bandwidth, and energy. Trends show reliance on DNN-based SR, lightweight architectures, and AI-driven resource management [1, 6, 4]. Despite advancements, challenges in real-time processing, energy efficiency, and scalability persist, often due to inherent system trade-offs [5, 11]. Continued innovation in adaptive SR, AI decision-making, and hardware co-design is essential, driving the future of efficient, high-quality, accessible streaming.

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