Video Upscaling in Extreme Edge Environments

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***Abstract*—As digital media consumption skyrockets, there is an escalating demand for superior video streaming quality in settings with varied internet connectivity and restricted bandwidth. Addressing this challenge, our research introduces the Extreme Edge-enhanced Streaming (EEDES) scheme, capitalizing on the underutilized resources of edge devices like smartphones, laptops, and connected vehicles. This approach harnesses edge computing alongside machine learning to enhance low-bitrate video frames to higher resolutions. By segmenting video frames into smaller sub-frames, our method distributes the processing tasks across a network of available edge devices. This strategy employs a Super-resolution (SR) machine learning technique to execute tasks on these devices, maximizing their computational potential.**

***Index Terms*—Edge Computing, Extreme Edge, Super-resolution, Quality of Service**

I. Introduction

With the rapid rise of the Internet of Things (IoT) and digital media, the demand for high-quality video streaming is intensifying. By 2025, the number of IoT devices is expected to exceed 75 billion [1], significantly straining network and computing resources and challenging the maintenance of quality service in the face of diverse connectivity and bandwidth issues. Edge Computing (EC) addresses these challenges by decentralizing data processing to devices like smartphones and laptops, reducing dependency on distant data centers and potentially lessening latency and network congestion [2].

Our research utilizes edge computing and machine learning-based Super-resolution (SR) techniques to enhance video streaming quality [3]. This approach leverages the untapped computational power of edge devices to improve the resolution of video frames under bandwidth constraints, thus expanding access to high-quality video across different network conditions. Additionally, we implement a replication strategy to enhance system reliability, distributing tasks across multiple devices to compensate for potential device failures or unavailability. This method not only ensures consistent service but also adapts to variations in device performance and network states, demonstrating the efficiency and scalability of distributed SR techniques in enhancing video streaming quality.

II. Related Work and Motivation

Research in enhancing video quality within bandwidth-restricted environments has seen considerable advancements, particularly through the integration of Super-resolution (SR) and edge computing (EC). Notably, deep learning-driven SR techniques, such as those demonstrated by Xintao Wang et al. with the Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN), have significantly advanced the field. ESRGAN, with innovations like Residual-in-Residual Dense Blocks and a relativistic GAN approach, has improved texture detail and realism, reducing visual artifacts and setting new benchmarks in the PIRM2018-SR Challenge [4].

Edge computing also contributes significantly to video quality enhancement, with frameworks like LiveSR and edge-SR (eSR) leveraging the computational power of edge devices. LiveSR uses network edge-based deep neural network SR to boost video quality while minimizing backhaul network load, particularly effective in 5G settings [5]. Similarly, Michelini et al.'s eSR is tailored for real-time applications on resource-limited devices such as smartphones and smart TVs, balancing quality with efficiency [6].

There remains a need to better distribute SR tasks across multiple edge devices to enhance video streaming in bandwidth-limited areas. Current research hasn't fully tapped into distributed video enhancement tasks, which could significantly improve video quality in real-time without high-speed internet.

III. Extreme Edge enhanced Streaming (EEDES)

The system architecture involves a process where an orchestrator plays a central role in enhancing video quality through the use of edge computing. Initially, low-bitrate video frames are sent from the user's device to the orchestrator. Upon receiving these frames, the orchestrator splits each frame into smaller sub-frames. It then assesses the required number of edge workers needed for the task.

Once the orchestrator determines the number of workers, it distributes the sub-frames among containerized edge workers. These workers process the sub-frames to perform SR tasks, transforming them into higher-resolution versions. After processing, the super-resolved sub-frames are sent back to the orchestrator.

In the final step, the orchestrator combines the high-resolution sub-frames to reconstruct the complete enhanced output frame. This high-resolution frame is then sent back to the user's device, providing a better video viewing experience despite the original low bitrate and bandwidth constraints. This efficient system architecture ensures minimal latency and optimizes computational resources across the network.

(a) Ground truth image from the test set. (PI = 1.92)

(b) 4× downsampled image. (PI = 5.33, PSNR = 25.57)

(c) Super-resolved image. (PI = 2.05, PSNR = 24.09)

Figure 1: Showcasing of SR results on three images from the PRIM dataset [7], compared against the ground truth.

IV. Performance Evaluation

In this section, we evaluate the EEDES system by assessing the quality of super-resolved images, ensuring the frame-splitting process does not degrade them. We use both visual assessments and two key performance metrics for this quantitative evaluation: Peak Signal-to-Noise Ratio (PSNR) [8], which measures the quality against the ground truth, and Perceptual Index (PI), which evaluates image quality without a reference image, as introduced by the PIRM challenge [7].

A. Dataset

We conducted an evaluation of the proposed EEDES scheme using the well-known PIRM-SR dataset [7], specifically employing its test set. This dataset is recognized for setting the initial benchmark for SR algorithms that prioritize perceptual quality. The novel evaluation approach described in [7] facilitates the assessment and comparison of perceptual SR methods alongside those designed for maximizing PSNR. Our evaluation involved measuring the PSNR and PI for 300 low-resolution images processed through the EEDES scheme.

B. Simulation Results and Analysis

Fig. 1 presents a comparison of three images from the PRIM dataset to evaluate the effectiveness of the EEDES scheme. It includes a ground truth image, a 4x downsampled image, and a super-resolved image. The ground truth has a PI of 1.92, indicating high quality, while the downsampled image shows notable degradation with a PI of 5.33 and a PSNR of 25.57. The super-resolved image, enhanced by the EEDES scheme, significantly improves in perceptual quality with a PI of 2.05 and a PSNR of 24.09, nearing the ground truth's quality. These results demonstrate the EEDES scheme's capacity to restore detailed textures and quality in images that have undergone significant quality loss due to downsampling, proving its potential for practical applications where high fidelity and perceptual quality are essential.

V. Conclusion

This paper presented the Extreme Edge-enhanced Streaming (EEDES) scheme, which combines edge computing and sophisticated machine learning to improve video streaming in environments with limited bandwidth. Our tests with the PRIM dataset showed considerable enhancements in video quality, validating the efficacy of distributed Super-resolution (SR) techniques. Future research will aim to enhance scalability, incorporate advanced machine learning models for better video upscaling, and refine techniques for accurately determining the necessary number of task replicas based on different factors.

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