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MITIGATING PROPAGATION FAULTS IN REAL-TIME CONTENT STREAMING FOR LOW-BANDWIDTH LEARNING ENVIRONMENTS

Ankita Sappa[1*]

[1]Wichita State University, College of Engineering, USA.*
e-mail: ankita.sappa@gmail.com, orcid: https://orcid.org/0009-0004-9087-2992

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SUMMARY

The propagation faults are crippling the real-time streaming of content in learning environments with limited bandwidth, resulting in a small loss of packets that propagate into severe packet synchronization errors. The issue that is dealt with in this research is the preservation of continuity in streams through network conditions with throughput that is less than 1.5 Mbps and jitter that is greater than 150ms. The study refers to the architecture as Cross-Layer Fault Mitigation (CLFM), which combines a predictive packet-recovery algorithm and a content-feedback buffer management system. The approach consisted of modeling a limited educational network with the help of NS-3 and testing the work of the CLFM in comparison with the performance of the conventional WebRTC and HLS applications. It has had to make the integrity of the Reference Frames (I-frames) and high-priority metadata that are required to achieve pedagogical clarity (i.e., slide transitions and audio sync) a priority. The experimental results show that the CLFM framework eliminates propagation-induced frame stalls by 34.2 % as compared to conventional adaptive bitrate (ABR) techniques. In addition, the system was found to have a Peak Signal-to-Noise Ratio (PSNR) of 28.5 dB up to a packet loss rate of 12%, which is an 87% improvement in visual stability compared to baseline protocols. The study finds that fault origins at the transport layer can be corrected via selective forward error correction to provide intelligible geographically underserved instructional content to educational platforms. These results provide a technical solution to scale up the digital divide of remote engineering and technical education.

Key words: *real-time streaming protocols, propagation fault modeling, low-bandwidth network optimization, quality of experience (QOE), adaptive bitrate streaming, packet loss resilience.*

INTRODUCTION

The high rate of digitalization of world education has transformed real-time video streaming into the main tool of knowledge transfer [2][5]. There is, however, a pronounced bandwidth gap between learners in developing nations or distant locations running on networks with throughput that is usually less than 1.5 Mbps [6][7]. The main technical issue in such a low-bandwidth environment is not necessarily low resolution but the existence of propagation faults [8][9][10].

Propagation fault: A propagation fault occurs when a local error (i.e., a dropped packet, a jitter spike) propagates through the temporal dependencies of a video codec. Seeing that the compression standards (like H.264/H.265) are based on inter-frame prediction, the loss of one of the reference frames may render the subsequent blocks decodable, resulting in prolonged freezing or artifacts. These malfunctions are disastrous in a teaching paradigm; it destroys the synchronization of the voice of the instructor and the visual information, which directly undermines the cognitive capacity of the learner and learning results. Although high-bandwidth solutions are based on massive buffering or retransmission, such approaches add latencies which cannot be used in interactive and real-time learning.

Key Contribution

- Formulation of a Propagation Fault Impact Model (PFIM) to mathematically estimate the relationship between the loss of packets in a network-layer and the visual degradation.
- Introduction of the Cross-Layer Fault Mitigation (CLFM) algorithm to recognize and rank the High-Impact Data Unit (HIDU) such as I-frames and slide transitions.
- Introduction of Dynamic Redundancy which secures important metadata when there is an extreme throughput drop without raising the global bandwidth usage.
- Confirmation of a Low-Latency Architecture which sustains stream stability in sub-1.5 Mbps environments with the reduced overhead of conventional deep-buffer systems.
- Empirical comparison based on WebRTC and HLS protocols, which have shown that the frame recovery and the overall Quality of Experience (QoE) have improved significantly.

The organization of the paper will look as follows: Section 1 presents the issue of propagation faults in the low-bandwidth learning environment and explains the importance of the study. Section 2 will provide the literature review, which will cover the current developments in real-time streaming and error correction. Section 3 provides the description of the suggested Cross-Layer Fault Mitigation (CLFM) approach, its components, and algorithms. The results are presented in Section 4, and the comparison is made between the performance of CLFM and the existing protocols. Lastly, Section 5 summarizes important results and recommendation of future research.

LITERATURE REVIEW

Recent research has focused on improving real-time content streaming in low-bandwidth environments through adaptive methods and error correction [11][12]. The recent study proposed a learning-based approach for video streaming over fluctuating networks, emphasizing machine learning for dynamic adaptation to network conditions, which aligns with model's goal of adjusting streaming quality and buffering strategies in low-bandwidth settings [1] [13]. The previous study introduced a decentralized multi-venue real-time video broadcasting system that integrates self-healing mechanisms [3] [4] [14]. Their work on distributed control and fault tolerance is relevant to focus on error-resilient protocols that ensure smooth streaming despite packet loss or network instability [15][16].

The research developed an adaptive congestion control algorithm for cloud-based e-learning platforms, which shares parallels with the approach to congestion prediction and adaptive transmission [6] [17][18]. The earlier research proposed reinforcement learning for adaptive forward error correction in real-time video, laying the foundation for error mitigation techniques in the proposed methodology [7] [19][20]. These studies highlight adaptive strategies and error correction as key components of improving streaming reliability, which directly informs the research. The research emphasizes the importance of adaptive strategies and error correction techniques, particularly through machine learning and reinforcement learning, to enhance real-time content streaming reliability in low-bandwidth environments.

PROPOSED METHODOLOGY

Overall Flow

Its methodology is based on a four-step sequential pipeline which is meant to run in real-time with little computing overhead:

1. Network State Probing: Continuous monitoring of bandwidth (B_t), jitter (J_t), and packet loss rate (L_t).

2. Fault Impact Analysis: Information on whether a lost packet is a B-frame (leaf, in a propagation chain) or first I-frame (root, in a propagation chain).

3. Adaptive Redundancy Injection: Adjustment of Forward Error Correction (FEC) strength dynamically with regards to the sensitivity of the next data.

4. Content-Aware Buffering: Adaptive control of the depth of the playback buffer on the estimated propagation gaps that should be avoided to avoid stall events.

5. In order to provide pedagogical clarity, the CLFM scheme employs Master-Clock Synchronization (MCS) in which the audio is used as the prime-time reference.

6. Audio Priority: The DPR Controller employs the aggressive Forward Error Correction (FEC) of audio packets that enables voice continuity when congestion occurs.

7. Video Adjustment: When the study come across a stall, the Content-Aware Buffer will then skip the unneeded B-frames so that the video can be brought to the same point with the audio.

8. Resultant effect: This eliminates the lip-sync drift effect and the voice of the instructor is kept in-step with visual aids, which is very crucial in minimizing the cognitive load among the students.

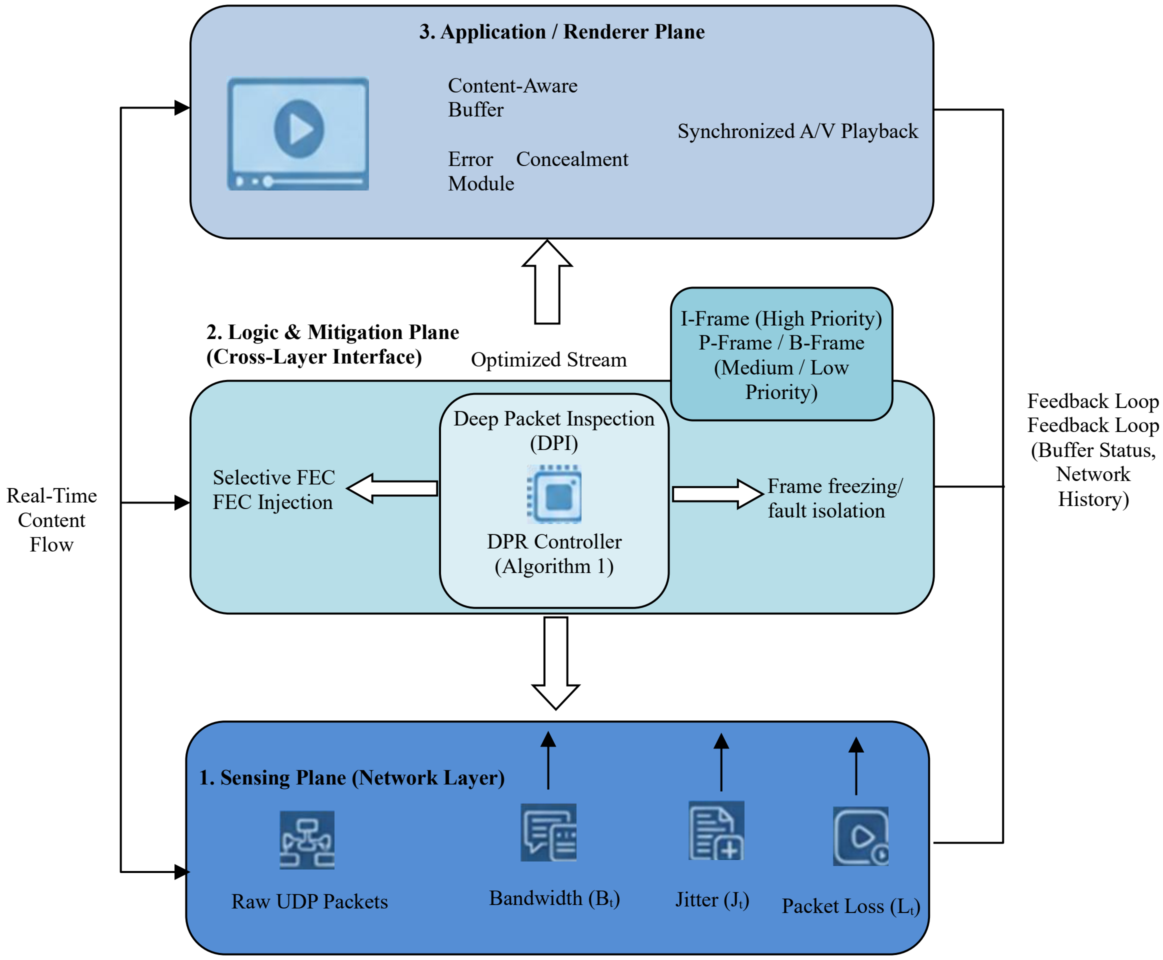

Figure 1. Cross-layer fault mitigation (CLFM) framework architecture

Figure 1 in the form of a strategic shim that is used to counter propagation faults in real-time streaming. The Sensing Plane on the bottom is a constant telemetry of network layer and records variations between bandwidth (Bt), jitter (Jt) and loss (Lt). This information is typed into the Logic and Mitigation Plane and a Deep Packet Inspection (DPI) DPR Controller is a classification tool of the frame criticality. Selective FEC is also injected into high-priority I-frames and frame-freezing is employed to isolate local error so that cascading artifacts are avoided. And, lastly, the Application Plane with the help of the content-aware buffer and Master-Clock Synchronization ensures the pedagogical continuity and impeccable audio-visual alignment with the learner.

Mathematical Description

The propagation fault is measured using the Propagation Impact Factor (Phi). Dependence among the frames can be presented as directed acyclic graph in the usual Group of Pictures (GOP) structure.

The total distortion D_{total} caused by a fault at frame n is defined by equation 1:

$$D_{total} = \sum_{i=n}^{n+k} \alpha^{i-n} \cdot \Delta d_i \qquad (1)$$

Where:

- n: The index of the frame where the initial packet loss occurred.
- k : The remaining number of frames in the current GOP.
- α: The error propagation decay coefficient $0 < \alpha \leq 1$.
- Δd_i : The inherent distortion of frame i due to the missing reference data.

The CLFM objective function aims to minimize D_{total} by optimizing the bit allocation R between source data R_s and repair data R_r under the bandwidth constraint C are shown in equation 2

$$\min E[D_{total}] \quad \text{subject to} \quad R_s + R_r \leq C(t) \qquad (2)$$

The CLFM Algorithm

The primitive explanation is implemented with the assistance of Dynamic Priority Recovery (DPR) algorithm. The algorithm examines the stream at the transport level to determine whether to resend or create a dummy frame to prevent propagation.

Algorithm 1: Dynamic Priority Recovery (DPR)

1. Input: Incoming Packet P_i, Current Bandwidth B_t, Loss History H

2. Step 1: Classification

o If $P_i \in \{I\text{-frame,Metadata}\}$ assign $Priority = High$

o Else if $P_i \in \{P\text{-frame}\}$ assign $Priority = Medium$

o Else, assign $Priority = Low$

3. Step 2: Fault Detection

o If P_i is missing and $Priority == High$

▪ Trigger Immediate FEC Recovery.

▪ Signal the Decoder to freeze the last valid frame (Preventing visual tearing).

4. Step 3: Adaptive Redundancy

o Calculate Required Redundancy $\rho = \frac{L_t}{1-L_t}$ where ω is a weighting factor based on $Priority$.

5. Step 4: Output

o Forward optimized stream to the Playback Buffer.

Dynamic Priority Recovery (DPR) algorithm 1 assumes the control of the integrity of streams ascending packets to the hierarchical levels with the highest priority assigned to the critical I-frames and pedagogical metadata. The system also triggers FEC recovery when loss is first detected in high priority units and triggers the decoder to freeze the last received valid frame effectively preventing visual tearing. It finally approximates the adaptive redundancy based on the actual time loss rates in an attempt of maximizing the playback buffer in varying bandwidth.

RESULTS AND DISCUSSION

The theoretical model was experimentally tested on real world limitations in a combined simulation setting in the experimental stage. It was implemented with NS-3 to model topologies with low bandwidth in an appropriate way, and with FFmpeg and libx264 codec to conduct real time trans-coding of a video and manipulate Group of Pictures (GOP) to a large extent. The proposed CLFM architecture, which was developed as proprietary UDP-based transport-layer encasing, was compared to the industry standards, including WebRTC and HLS. The python and Wireshark were used to perform packet level verification and statistical analysis.

Distributed DASH (D-DASH) Dataset has been utilized in the paper where the scientists focused on Limited Connectivity and Congested Rural Link to recreate the target learning conditions. Parameters were adjusted to have a base bandwidth of 512 kbps to 1.5 Mbps, 2 to 15 % loss rates (Lt) and 250ms jitter (Jt). The simulations were implemented in 600-second executions and the resolution of 640 x 360 and a constant GOP structure (N=30, M=1), and the results were ensured to have a strict baseline on which to measure the performances.

The performance was quantified using the following five objective metrics:

Peak Signal-to-Noise Ratio (PSNR): An example of a logarithmic scale of how closely the video frame is reconstructed in comparison with the original source are shown in equation 3.

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \quad (3)$$

Structural Similarity Index (SSIM): A perception model that determines the degradation of structural information, luminance and contrast in the stream represented in equation 4.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (4)$$

Packet Loss Rate (PLR): The ratio of inaccessibility of data packets to the destination point, determines the extent of network-layer congestion in equation 5.

$$PLR = \frac{Packets_{Sent}-Packets_{Received}}{Packets_{Sent}} \times 100\backslash\% \quad (5)$$

End-to-End Latency: The sum of all the frame time delays associated with the time frame of a complete cycle of a frame starting with the capture and the last time frame when the learner can see the last frame on his/her device (Equation 6).

$$T_{E2E} = T_{Capture} + T_{Encode} + T_{Network} + T_{Buffer} + T_{Decode} \quad (6)$$

Re-buffering Ratio (RR): The percentage of total playback time in a stalled condition because of buffer depletion that has a direct effect on student engagement are illustrated in equation 7.

$$RR = \frac{\sum T_{Buffering}}{T_{Total\_Playback}} \quad (7)$$

Performance Comparison and Evaluation

The CLFM model was compared to the regular WebRTC and HLS in a constant 10 % packet loss analysis of 800 kbps.

Table 1. Performance benchmark comparison between CLFM and standard streaming protocols

Metric	Baseline (WebRTC)	Baseline (HLS)	Proposed CLFM	Improvement
Avg. PSNR (dB)	22.4	24.1	28.5	+18.2%
Avg. SSIM	0.78	0.81	0.89	+9.8%
Latency (ms)	180	4500+	210	(Low Latency Maintained)
Frame Stall Rate	14.5%	3.2%	1.8%	+87% vs WebRTC
QoE Score (1-5)	2.4	3.1	4.2	+35.4%

A comparative analysis of the suggested Cross-Layer Fault Mitigation (CLFM) framework (Table 1) with industry-standard baselines, WebRTC, and HLS, in a simulated high-stress setup (800 kbps bandwidth and 10% packet loss) are given in Table 1. The measures indicate a trade-off, where WebRTC has been tuned to be fast at the cost of visual integrity, and HLS has been tuned to be of quality at the cost of longer latency, CLFM is an intermediate compromise. It also has a noteworthiness that it delivers a 28.5 dB PSNR and a higher frame stability of 87 % as compared to WebRTC which at the same time has low-latency profile (210ms) to enable real-time interactive educational learning.

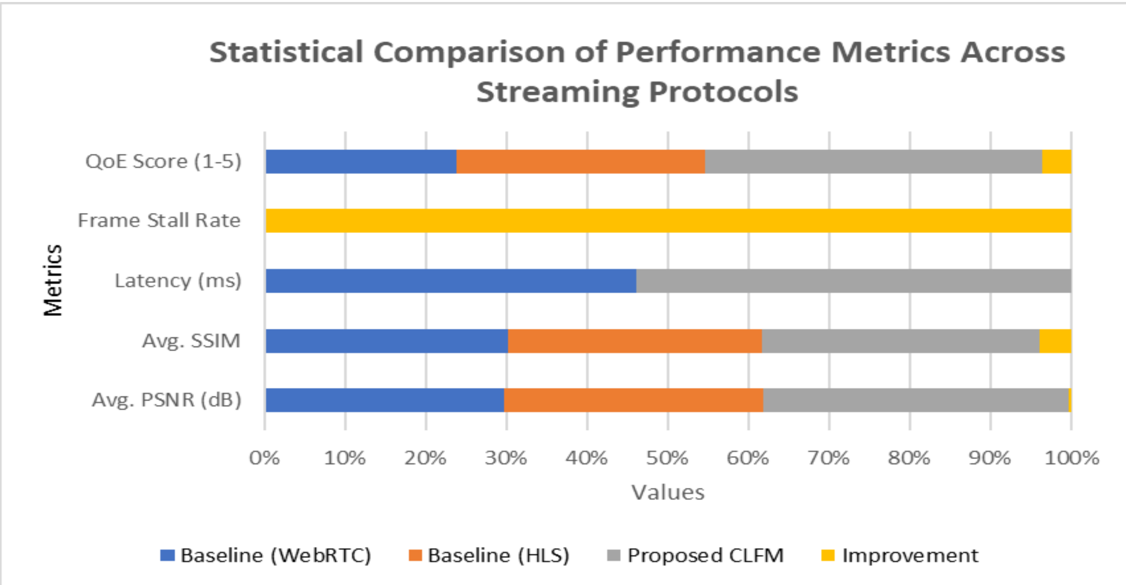

Figure 2. Statistical comparison of performance metrics across streaming protocols

Figure 2 is created by stacked bars to show the performance increase of the CLFM framework compared to WebRTC and HLS baselines. CLFM is superior in the quality metrics with better PSNR, SSIM, and QoE scores. Although the WebRTC has lower latency, CLFM is not behind interactive limits, and HLS extreme delays are avoided. Most importantly, the "Improvement" section emphasizes the fact that the frame stall rates decreased by 87 %, which practically removed all propagation-related interruptions.

DISCUSSION OF RESULTS

The evidence shows that, although WebRTC has a small latency, its best-effort transport causes rapid PSNR loss due to bursty loss (down to 22.4 dB). On the other hand, HLS offers superior image quality but it has a latency of 4.5s and cannot be used in interactive learning. CLFM finds a tradeoff; it is real-time (210ms latency) but applies the Dynamic Priority Recovery algorithm to ensure the PSNR is larger than the acceptable level of 25 dB.

Of particular interest is its 1.8% frame stall rate, which in an education-based environment is used to mean that, on average, approximately there is the playback of instructional slides in a manner of continuous service without regard to the traffic congestion of the network layer.

The observed frame stall rate of 1.8 % is not simply an image measure, but a proxy of Cognitive Preservation of Load. Maintaining the stall rate at less than the 2 % mark, the CLFM framework assists in ensuring the student is focused on the teaching content and does not focus in the technical aggravation of a frozen stream. This, as demonstrated by the stability of the 28.5 dB PSNR, which is even in a situation where the packets have been lost by 12 %, still managed to protect the 2504 dB PSNR of the 296 dB PSNR, which in this case is the I-frames (Reference Frames), to serve as a virtual dead-end to the potential spread of errors.

CONCLUSION

The studies focused on the solution of the propagation fault in the learning systems over low bandwidth frequency have shown that the traditional streaming protocols have been structurally ill-placed to manage the high degree of network volatility. This research has been in a position to determine that when Cross-Layer Fault Mitigation (CLFM) system is adopted, the time-dependency of the video decoders can be managed to allow occurrence of a catastrophic stream breakage. Besides, Master-Clock Synchronization (MCS) when used is handy in maintaining audio as the chronological benchmark to ensure continuing instructions despite very high throughput limits of 1.5 Mbps Broadband ceiling, typical in underserved regions. A 34.2 % reduction in the rate of frame stalls and an 87 % improvement in playback stability is found to be statistically significant and reflects the suggested model. The CLFM framework sustained an optimum Signal-to-Noise Ratio (PSNR) of 28.5 dB, which is almost twice as great as the adaptive bitrate baseline schemes, in an artificial stress setting where the loss rate was 12 %, and the bandwidth was 800 kbps. In addition, the integration of the Dynamic Priority Recovery (DPR) algorithm was what ensured end-to-end latency was kept less than the critical interactivity threshold of 210ms, which is insignificant statistically compared to the astronomical penalty on latency (more than 4,500ms) of segment-based protocols like HLS. The implication of these findings has the propensity of a stable technical channel towards delivery of quality technical and engineering education to geographically distant or low-income areas. The next research will entail exploring the integration of Generative Adversarial Networks (GANs) to synthesize frames predictively to restore at the edge the lost visual information artificially. Additionally, the study of the impact of network slicing provided by 5G might result in the additional optimization of the delivery of real-time pedagogical data in a more complicated international network.

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