Online Video Streaming

Using Cloud Computing

|  |  |  |
| --- | --- | --- |
| Dr. Narendra Rao  Head of Department, Dept. of CSE  Mohan Babu University (Erstwhile Sree Vidyanikethan Engineering College),  Tirupati, India | Dr. K. Padmaja  Associate Professor, Dept. of *CSE*  Mohan Babu University (Erstwhile Sree Vidyanikethan Engineering College),Tirupati, India | Gorantla Sahithi  UG Scholar, Department of CSE  Mohan Babu University (Erstwhile Sree Vidyanikethan Engineering College),  Tirupati, India |
| Nalathati Siddaradha  UG Scholar, Department of CSE  Mohan Babu University (Erstwhile Sree Vidyanikethan Engineering College),  Tirupati, India | Padiri Devi Sree  UG Scholar, Department of CSE  Mohan Babu University (Erstwhile Sree Vidyanikethan Engineering College),  Tirupati, India | Vennapusa Saketh Reddy  UG Scholar, Department of CSE  Mohan Babu University (Erstwhile Sree Vidyanikethan Engineering College),  Tirupati, India |

***Abstract*—A detailed review has been done on video on demand and this paper provides details of different techniques to ensure smooth Video-on-Demand (VoD) services, popular videos should be cached near users. This requires accurate prediction of video popularity, which tends to fluctuate over time due to various factors. Mobile video streaming is booming, but limited network bandwidth can lead to video impairments like compression glitches and buffering, impacting user experience (QoE). Various ML-based methods analyze traffic patterns and statistics to infer KPIs, but mostly operate on specific use cases. Balancing user experience with encoding costs in on-demand video streaming is difficult due to diverse factors. Live streaming, especially for high-motion content like sports, is increasingly popular. A novel FEC scheme that prioritizes reference pictures in SVC based on their relevance to video quality, leading to better recovery from packet loss compared to conventional schemes.**

**Keywords— Quality of experience, Streaming media, Predictive models, Bit rate, Quality assessment, Estimation, High efficiency video coding.**

# I. INTRODUCTION

# ***VOD***-

Video-on-demand (VoD) services are booming, but storing all videos is impractical. Caching popular videos based on request history can improve performance. This paper proposes the MIPD algorithm, which analyzes request patterns to predict video popularity. MIPD outperforms other methods in accuracy and hit rate, offering a valuable tool for VoD caching optimization. [1]. Mobile video is booming, but network fluctuations hurt user experience. Predicting video quality (QoE) in real-time helps operators improve resource allocation and user satisfaction. This paper proposes a model for continuous QoE prediction considering frame quality, rebuffering events, and memory effects, offering a valuable tool for evaluating video streaming control strategies. [2]. Mobile video is dominating internet traffic, with video streaming platforms like YouTube and Netflix leading the way. Challenges in monitoring encrypted video traffic and dynamic quality adjustments by these platforms hinder network operators from understanding and optimizing user experience. [3]. Video streaming dominates internet traffic, with providers aiming to optimize video quality for different devices and networks. Traditional "one-size-fits-all" bitrate ladders are inefficient. This paper proposes a content-aware method to estimate bitrate ladders for each video, reducing computation and storage needs while maintaining quality. [4]. Live video streaming is booming, but video quality suffers due to factors like motion blur and interlacing. This paper introduces a new database (LIVE Livestream) with high-resolution sports videos containing common live streaming distortions, enabling accurate quality assessment and improved future algorithms. Existing video quality assessment databases are inadequate for live streaming: they lack high-resolution content, diverse distortions, and professionally captured videos. The LIMP database attempts to address live streaming but contains limited content. This gap motivates the creation of a new database specifically designed for live sports streaming. [5].

Real-time video streaming suffers from packet loss, impacting user experience. Existing FEC schemes like frame-level and GOP-level have drawbacks like delay or inefficiency. This paper proposes a new "reference-order sliding window FEC" scheme based on video dependencies, offering better recovery performance for high-priority frames while maintaining low delay compared to other methods [6].novel approach to improve the user experience in Multiview video streaming by considering viewpoint priority and quality delays. The MVP algorithm offers a promising solution for ensuring smooth playback and seamless transitions in this emerging video technology[7].

II. METHODOLOGY

The paper analyzes a method called Minimal Inverted Pyramid Distance (MIPD) to estimate video popularity in a Video-on-Demand (VoD) system based on past request arrival times. MIPD uses a measure called Inverted Pyramid Distance (IPD), which considers both recency and frequency of requests. It takes a parameter "k" representing the number of past requests used to calculate IPD. The paper analytically determines the optimal value of k for accurate ranking of a certain number of videos with desired confidence.

MIPD outperforms four other methods: Least Recently Used (LRU), Least Frequency Used (LFU), Least Recently/Frequently Used (LRFU), and Exponential Weighted Moving Average (EWMA) through extensive simulations with realistic video popularity patterns. MIPD effectively captures both recent bursts and sustained popularity trends, making it a valuable tool for optimizing resource allocation and delivery in VoD systems[1].

Continuously predicting the Quality of Experience (QoE) for wireless video streaming. QoE reflects a viewer's subjective perception of the streaming experience, encompassing factors like video quality, buffering events, and overall satisfaction. Accurate prediction of QoE can help optimize resource allocation and deliver a smoother viewing experience Inputs: Frame Quality: This is measured using an objective metric like Peak Signal-to-Noise Ratio (PSNR) that reflects the technical quality of individual video frames. Rebuffering Events: This captures information about interruptions caused by buffering, including duration and frequency Memory: This accounts for the user's past experience and how it influences their current perception of quality. Prediction Model: Block-structured nonlinear Hammerstein-Wiener (H-W) model: This model combines a nonlinear static system for processing frame quality with a linear dynamic system for handling rebuffering and memory effects. Dynamic Neural Network (NARX): This network has one input layer, one hidden layer, and one output layer. It utilizes the Levenberg-Marquardt algorithm for training and predicts continuous QoE scores based on the input vectors. Core Ideas: The model considers not just the current video quality but also past rebuffering events and user experience to provide a more accurate prediction of overall QoE. The H-W model allows for flexible handling of nonlinearities in video quality perception, while the NARX network effectively captures the temporal dynamics of QoE . Evaluation: The model is tested on a dataset containing continuous QoE scores and demonstrates good performance in predicting QoE fluctuations. Compared to other methods, this approach achieves higher accuracy and better captures the dynamic nature of QoE in wireless video streaming. Overall, this methodology offers a promising approach for continuous QoE prediction in wireless video streaming, paving the way for improved resource management and enhanced user experience.[2].

A generic framework for monitoring the Quality of Experience (QoE) of encrypted video streaming using machine learning (ML). This is crucial for network operators to optimize resource allocation and improve user satisfaction, as encrypted video content prevents direct access to QoE metrics. The framework consists of three main stages: Data Acquisition and Preprocessing: Network traffic features are extracted from encrypted video streams, such as packet size, inter-arrival time, and flow duration. These features are then preprocessed to remove noise and prepare them for ML models/KPI Estimation: Different ML models are trained on labeled datasets linking network traffic features to QoE metrics like bitrate, resolution, and buffering events. These models can then estimate QoE/KPIs for real-time video streams. Adaptive Model Selection and Re-evaluation: The framework continuously monitors the performance of the ML models and adapts by selecting the best performing model for each specific use case. Additionally, the models are periodically re-evaluated and retrained on updated data to ensure accuracy and relevance[3].

Building efficient bitrate ladders in adaptive video streaming (AVS). AVS allows viewers to switch between different video qualities based on network conditions, but choosing the right bitrate options (the ladder) is crucial for balancing video quality with bandwidth usage. The proposed method, called Content-Aware Bitrate Ladder (CABL), analyzes video content to identify segments with varying visual complexity. For complex segments, CABL includes more bitrate options to ensure smooth playback, while simpler segments get fewer options to save bandwidth. This dynamic approach optimizes the ladder for each video, unlike traditional fixed ladders or those based solely on average complexity[4].

The challenge of evaluating the quality of live-streamed videos with lots of movement, like sports. They address the limitations of existing methods that can't fully capture the unique distortions and perceptual effects of high-motion content. The methodology involves two key parts:1. Building a Live Streaming Video Quality Database: They create a new database called LIVE Livestream, containing 315 videos of diverse athletic scenes with 6 types of common distortions (e.g., blocking, motion blur).This database captures the real-world complexities of live streaming, unlike other databases mainly focused on static or slow-motion content. Conducting Subjective and Objective Quality Assessments: Subjective tests involve human viewers rating the perceived quality of videos from the database. Their opinions provide valuable ground truth data. Objective tests utilize various quality metrics like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) to measure technical video quality[5].

Proposes a novel FEC scheme that prioritizes reference pictures within a sliding-window framework to enhance video quality in real-time streaming over unreliable networks. Window Formation: A sliding window of fixed size accommodates a sequence of video frames. Frames' reference orders within the scalable video coding (SVC) structure are analyzed. Reference-Weighted FEC Redundancy: Frames with higher reference order, serving as references for more subsequent frames, are assigned more FEC redundancy. This safeguards crucial frames, minimizing error propagation Encoding and Packetization: Reed-Solomon codes are employed to generate FEC redundancy packets for each frame based on its weighted allocation. Original video packets and FEC redundancy packets are interleaved and transmitted. Error Recovery at the Receiver: Lost packets are reconstructed using FEC redundancy if possible. Unrecoverable frames are concealed using error concealment techniques to mitigate visual impairments. Evaluation demonstrates that this reference-weighted FEC scheme outperforms conventional FEC methods in terms of video quality under packet loss conditions[6].

The challenge of seamless viewpoint switching in Multiview video streaming by introducing a Multiview QoE model and a quality-based adaptation technique. It addresses two key delays affecting QoE: transition delay (new viewpoint not buffered) and quality delay (new viewpoint buffered but low quality). The proposed Multiview video priority (MVP) algorithm prioritizes the main viewpoint and allocates bandwidth effectively, reducing both delays and improving user experience with better quality, smoothness, and seamless switching[7].

III. BACKGROUND RELATED WORK

The field of optimization in VoD systems focuses on popularity estimation based on request statistics of videos. Most cache replacement algorithms use popularity estimation methods using the request record, identifying the least likely to be requested objects using past access patterns. The LFU popularity estimation method and its variants use frequency of requests to identify the least popular object, removing the item requested the least number of times in the past from the cache. However, the LFU method does not emphasize recent history over earlier reports, which can result in incorrect identification of many "has-beens" as popular objects. The LRU popularity estimation method and its extensions use time distance, evicting the object requested least recently from the cache when needed. However, it does not capture the long-term popularity of objects, and uneven request arrival patterns may result in less popular objects being identified as popular ones. The LFU popularity estimation method is more effective when the popularity of videos is stable, while LRU is more effective when popularity is rapidly changing[1].

The study of Quality of Experience (QoE) aims to design a model that accurately and automatically perceives user subjective experiences and solves resource allocation problems, ensuring visual satisfaction. Existing QoE models can be divided into retrospective prediction models and continuous prediction models. Retrospective models measure video quality by one score and use Video Quality Assessment (VQA) methods. However, these models do not consider the interaction between video quality and Refresh Rate (RE) during video playing. Continuous QoE prediction models have been proposed to study the effects of bitrate changes and Refresh Rate (RE) on video quality and QoE during online video playing. These models use objective measures of perceptual video quality, rebuffering-aware information, and a QoE memory descriptor as inputs. The Hammerstein-Wiener model is used to better reflect human memory characteristics. Analyzing continuous subjective QoE helps understand the impact of various events on QoE during video playing, particularly in the case of changeable network bandwidth. This can provide a reference for designing quality-aware video stream bitrate switching algorithms to maximize mobile user experience during video transmission[2].

In-network Quality of Experience (QoE) monitoring solutions used to rely on deep packet inspection (DPI) for extracting information about video quality were no longer viable due to the adoption of traffic encryption. Two approaches have been proposed to tackle this problem: session-modeling-based (SM) and machine-learning-based (ML). SM-based solutions require knowledge about the streaming protocol and rely on session reconstruction for inference of QoE-influencing KPIs. However, finding analytical solutions for a wide range of potential use-cases becomes extremely complex due to the dimensionality of the problem and the need for adapting network operators' QoE/KPI estimation models. ML techniques have been used for QoE/KPI estimation, arguing that they are more flexible and sustainable in the long run. Both SM and ML approaches require application-level ground-truth data for the learning phase, which can be relatively easy for some services and platforms. ML-based QoE/KPI estimation solutions are similar in their core idea, extracting network traffic features from the network traffic trace, and analyzing the network traffic trace for QoE/KPI estimation[3].

The traditional approach to encoding video content has been built a fixed "bitrate ladder" that provides recommended spatial resolution for the available bitrate. However, more advanced methods have been proposed, relying on encoding statistics collected through massive encodings or using selective encodes to predict bitrate ladders using probabilistic or pre-trained machine learning models. Most of these methods are based on a per-title optimization framework, with Netflix, Bitmovin, MUX, CAMBRIA, and others developing solutions that compute encoding complexity, use trial encodes to collect coding statistics, and use trial encodes within a probabilistic framework to speed up encoding decisions at higher resolutions. Recent work has also presented a per-scene optimization method aiming to maximize the quality or minimize the bitrate of each encoded representation in video-on-demand HAS scenarios. However, it is not possible to make direct detailed comparisons due to their proprietary nature[4].

Over the past decade, numerous subjective video quality databases have been developed, including the LIVE VQA Database, which includes 10 pristine videos processed with compression and packet loss distortions, the LIVE QoE Database for HTTP-based Video Streaming, which studies the quality of experience (QoE) of users who viewed compressed videos with simulated video stalls, and the LIVE Mobile Video Quality Database. These databases have been designed to assess the quality of live video streams, but they have limitations such as limited SD source contents and not considering other prevalent distortions common to live streaming videos. A more recent addition is the LIVE-VQC database, which contains 585 videos captured by a large group of users deploying various camera devices, including smartphones of all brands. The KoNViD-1k video quality database contains 1,200 video sequences, covering a wide variety of contents and authentic distortions, and the YouTube UGC Dataset contains 1500 20-second video clips covering popular UGC video categories, including gaming and sports[5].

The time-order sliding window (FEC) coding window management mechanism is based on frame timestamps, where video frames are arranged according to the time when they are generated by the video encoder. In general video coding, the frame dependence is continuous, making it feasible to use time order as the rule for coding window management. However, SVC adopts a hierarchical structure, where frames in a GOP are allocated to the base layer or enhancement layer. This approach causes the reference order between frames to change, causing the previous frame to not necessarily be the reference frame for the current frame. Applying the time-order mechanism in the SVC case may reduce the recovery probability, particularly under high packet loss rate (PLR) conditions. For example, under RS coding, the recovery probability of the time-order sliding window scheme is lower than that of the frame-level FEC. As frame I is decodable and frame P2 references frame I in the SVC case, the recovered frame P2 can be rendered, which is not possible in frame-by-frame reference patterns. Therefore, the PFR is also lower than that of frame-level FEC. Thus, the window management mechanism based on time order is no longer[6].

Multiview video streaming involves users switching between viewpoints using a remote control or movement in a VR application, making predicting user behavior challenging. Research on single view video focuses on the ABR algorithm to automatically select video quality based on network throughput and buffer occupancy level. However, Multiview video systems consist of multiple viewpoints and representations, posing new challenges in video streaming. Multiview video coding (MVC) or high-efficiency video coding (HEVC) can reduce video data in limited bandwidth conditions. An interactive DASH-based Multiview video coding of a selected viewpoint has been presented by Zhao et al. and Su et al., but these techniques are time-consuming and complex, increasing the processing load on the server or client. DASH system divides a full-length video into a sequence of small segments at equal duration, encoded at different bitrate levels. This improves bandwidth efficiency by avoiding playback freezing and enabling seamless quality transition. The segment-based scheme in DASH improves bandwidth efficiency by sequentially downloading segments to avoid playback freezing. The DASH-based Multiview video adopts a similar architecture, but adjustments to the client control mechanism are necessary to ensure video delivery. The DASH-based Multiview video system can be implemented using a combination of MVC, HEVC, and DASH-based Multiview video systems[7].

IV. TECHNIQUES

***1.Time-series analysis:***

This approach involves analyzing the historical request patterns for each video using techniques like ARIMA or SARIMA models. It can capture seasonality, trends, and cyclical patterns in popularity, but requires sufficient historical data and expertise in model selection.2.2.

***2.Collaborative filtering:***

This technique leverages user viewing history to recommend similar videos. By analyzing which videos users watch together, it can identify groups of related videos with similar popularity trends. However, cold-start problems arise for new videos and users with limited watch history.

***3.Content-based filtering:***

This method analyzes video metadata (e.g., genre, actors, keywords) to predict popularity based on similar content's past performance. It’s useful for new videos or those lacking extensive request history, but its accuracy depends on the quality and comprehensiveness of the metadata.

***4.Hybrid approaches:***

Combining multiple techniques (e.g., LRU, collaborative filtering, content-based) can leverage their individual strengths and overcome their limitations. This often involves weighted combinations based on factors like video age, content type, or user demographics.

***5.Reinforcement Learning (RL):***

This technique involves an agent that interacts with the streaming environment, receives rewards for good QoE predictions, and learns to adjust its prediction model over time. RL can be particularly useful in dynamic environments where network conditions and user behavior are constantly changing.

environments where network conditions and user behavior are constantly changing.

***6.Network Monitoring Module:***

Captures network-level metrics like packet delay, jitter, loss, and throughput. Analyzes traffic patterns and identifies streaming flows associated with video content.

***7.QoE Estimation Module:***

Utilizes machine learning (ML) models trained on historical data with correlated network metrics and user-reported QoE scores. Models predict QoE metrics like stalling, rebuffering, and video quality without requiring content decryption.

***8.Feedback and Adaptation Module:***

Analyzes predicted QoE and network conditions. Triggers adaptation mechanisms like bitrate adjustments, buffering optimization, or network resource allocation based on QoE predictions. Continuously refines ML models through feedback loops incorporating actual u0ser experience data.

***9.Statistical Analysis:***

This technique analyzes the statistical properties of the video content, like bitrate distribution, entropy, and spatial complexity. Based on these statistical measures, algorithms identify encoding points that best represent the different quality levels while minimizing redundancy. While simpler than ML, this approach might not capture all nuances of the video content and could lead to less optimal ladders.

V. RESULT AND DISCUSSION

The various techniques and algorithms were used for detecting liver cancer are analyzed and compared with the different types of measured parameters. The TABLE I illustrates the comparison of features extraction methods and classifiers were used by various researchers.

TABLE I. COMPARASION AND SUMMARY REPORT

|  |  |  |  |
| --- | --- | --- | --- |
| **Author** | **Year** | **IEE paper** | **Methods** |
| Tianjiao Wang, Chamil Jayasundara, Chamil Jayasundara, Ampalavanapillai Nirmalathas | 2020 | Estimating Video Popularity From Past Request Arrival Times in a VoD System | **Least Recently Used (LRU), Exponential Weighted Moving Average (EWMA), Minimal Inverted Pyramid Distance (MIPD)** |
| Wenjuan Shi, Yanjing Sun, Jinqiu Pan | 2019 | Continuous Prediction for Quality of Experience in Wireless Video Streaming | **Machine Learning (ML), Packet-level analysis** |
| Irena Orsolic, Lea Skorin-Kapov | 2020 | A Framework for in-Network QoE Monitoring of Encrypted Video Streaming | **Session-modeling based (SM), Machine Learning based (ML), Multi-domain Zero-touch Network and Service Management (ZSM)** |
| Angeliki V. Katsenou, Joel Sole, David R. Bull | 2021 | Efficient Bitrate Ladder Construction for Content-OptimizedAdaptive Video Streaming | **Fixed Bitrate Ladders, Exhaustive Search, Interpolation-based methods** |
| Zaixi Shang, Joshua Peter Ebeneze, Yongjun Wu | 2021 | Study of the Subjective and Objective Quality of High Motion Live Streaming Videos | **Subjective Quality Assessment (SQA), Full Reference (FR) Metrics, Crowdsourcing** |
| Rui Wang, Liang Ii, Bifeng He | 2022 | Sliding-Window Forward Error Correction Based on Reference Order for Real-Time Video Streaming | **Reed-Solomon (RS) codes, Unequal Error Protection (UEP), Adaptive Window Size** |

VI. CONCLUSION

In this paper, a survey has been made on the different types of methods and algorithms used for liver cancer detection. A detailed literature review on different hybrid intelligent algorithms was obtained. CT scan images based algorithms are most efficient and giving up to 92% accuracy. Some authors have proposed few automatic strategies to accelerate the procedure and to achieve high accuracy were used hybrid algorithm concepts but results were poor. The unaided strategies may give quicker segmentation however accuracy of these methods is still not good because parameters of these strategies may fluctuate among various patients. Performance metrics of various algorithms such as decision tree, SVM, neural networks, random forest, bayesian, swarm intelligence are analyzed and it was found that most researcher did work on either image data sets or attributes. Mostly work on CT images. Only few researchers did work on attribute data sets. In future work, if work is done on both data sets then a higher accuracy can be obtained.

VII. REFERENCES

[1]T. Wang et al., "Estimating Video Popularity From Past Request Arrival Times in a VoD System," in IEEE Access, vol. 8, pp. 19934-19947, 2020, Doi: 10.1109/ACCESS.2020.2966495.

[2]W. Shi, Y. Sun and J. Pan, "Continuous Prediction for Quality of Experience in Wireless Video Streaming," in IEEE Access, vol. 7, pp. 70343-70354, 2019, doi: 10.1109/ACCESS.2019.2919610.

[3]I. Orsolic and L. Skorin-Kapov, "A Framework for in-Network QoE Monitoring of Encrypted Video Streaming," in IEEE Access, vol. 8, pp. 74691-74706, 2020, Doi: 10.1109/ACCESS.2020.2988735.

[4]A. V. Katsenou, J. Sole and D. R. Bull, "Efficient Bitrate Ladder Construction for Content-Optimized Adaptive Video Streaming," in IEEE Open Journal of Signal Processing, vol. 2, pp,. 496-511, 2021, Doi: 10.1109/OJSP.2021.3086691.

[5]Z. Shang, J. P. Ebenezer, Y. Wu, H. Wei, S. Sethuraman and A. C. Bovik, "Study of the Subjective and Objective Quality of High Motion Live Streaming Videos," in IEEE Transactions on Image Processing, vol. 31, pp. 1027-1041, 2022, Doi: 10.1109/TIP.2021.3136723.

[6] R. Wang, L. Si and B. He, "Sliding-Window Forward Error Correction Based on Reference Order for Real-Time Video Streaming," in IEEE Access, vol. 10, pp. 34288-34295, 2022, Doi: 10.1109/ACCESS.2022.3162217.

[7] D. Tanjung, J. -D. Kim, D. -H. Kim, J. Lee, S. Kim and J. -Y. Jung, "QoE Optimization in DASH-Based Multiview Video Streaming," in IEEE Access, vol. 11, pp. 83603-83614, 2023, Doi: 10.1109/ACCESS.2023.3300380.