A survey on Measurement of Objective Video Quality in Social Cloud using Machine Learning

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Abstract - *Assessing objective video quality is critical in applications such as video streaming, video conferencing, and video surveillance. Although traditional subjective assessment methods are commonly used, they can be time-consuming and expensive. Objective methods for assessing video quality have been proposed, but often lack accuracy and consistency. In recent years, machine learning techniques, particularly deep learning models such as convolutional neural networks (CNNs), have shown promise for objective assessments of video quality. This study proposes a new method that CNN uses to understand the relationship between video characteristics and subjective quality judgments. The proposed method uses a large collection of video data evaluated by human observers to train CNN. The videos were then processed to extract quality-related features, which were used to train a machine learning model to predict objective quality outcomes. The model was tested on a separate set of videos, and the results showed that the proposed method achieved a high level of accuracy in predicting high quality objective outcomes. The results show that the proposed method achieves high accuracy and consistency in predicting subjective qualitative outcomes. Machine learning techniques can provide an objective assessment of video quality, which could benefit content creators, consumers, and service providers.*

Key Words: **Social Cloud, Quality of Experience (QoE), Convolutional Neural Network (CNN), Deep Learning, Video Quality Assessment, Peak Signal-to-Noise Ratio (PSNR)**

1. INTRODUCTION

The rapid advances in video technology and widespread availability of cloud-based social media platforms have led to a growing demand for the delivery of high-quality video content. Video content quality has a significant impact on user experience, and objective measurement of video quality is essential to ensure optimal user experience. Machine learning techniques are widely used to develop objective video quality measurement models that can automatically predict video quality based on various visual and perceptual characteristics. This approach has Several advantages over traditional metrics based on simplified measures such as pixel distortion or image Similarity. Machine learning algorithms can learn the complex relationship between video properties and perceptual quality, enabling accurate and robust quality predictions even in complex video environments. In social cloud applications, machine learning-based video quality assessment is particularly useful to optimize video transmission and distribution processes. By predicting the objective quality of video content, machine learning algorithms can optimize video bit rate, resolution, and other parameters to provide the best user experience while minimizing bandwidth usage. This paper aims to provide a comprehensive survey of the state-of-the-art in machine learning-based objective video quality measurement in the context of social cloud applications. An examination of recent studies that have used machine learning algorithms to evaluate video quality and compare the performance of different techniques in terms of precision, efficiency and scalability. The benefits and limitations of measuring video quality based on machine learning and identifying potential leads for future research. Overall, this article provides valuable insights into the state of the art for measuring video quality objectively and offers practical tips for improving video quality in social cloud applications using machine learning techniques.

2. TERMONOLOGIES

2.1 Video Quality Assessment

Video Quality Assessment (VQA) is a critical aspect of measuring the quality of videos. It involves the use of various techniques and algorithms to evaluate the perceptual quality of a video, based on various visual features such as sharpness, color accuracy, and contrast. VQA can be performed using subjective or objective methods. In subjective methods, human raters provide quality scores based on their perception, while objective methods use machine learning algorithms to estimate quality based on various metrics. VQA is important for video compression, streaming, and other applications where video quality is a critical factor.

2.2 Deep Learning

Deep learning is a powerful technique for measuring video quality, especially for objective evaluation. Deep learning algorithms like convolutional neural networks (CNNs) can extract visual features from videos that are difficult to quantify using traditional methods. These functions can be used to train models to predict video quality metrics such as structural similarity index (SSIM) and peak signal-to-noise ratio (PSNR). Deep learning can also be used to develop non-reference (NR) models to assess video quality that do not need a reference video for comparison. Deep learning has shown promise for improving the accuracy and reliability of objective video quality assessment models. . Video frames can be analyzed to predict video quality based on features extracted from them.

2.3 Convolutional Neural Networks (CNNs)

Video quality is often assessed using convolutional neural networks (CNNs) since they are capable of learning multi-layered visual cues from large data sets. CNNs consist of multiple layers of convolution filters that extract features from input data. In the context of video quality assessment, CNNs are used to extract visual features from video images and predict video quality. These characteristics can include sharpness, color accuracy, and contrast. Based on the visual characteristics of new videos, CNN can accurately predict their quality by training on a large set of video frames.

3. METHODOLOGICAL APPROACH

The measurement of objective video quality using machine learning typically involves the following methodologies:

- Dataset preparation: A dataset of videos with known quality scores is collected, along with corresponding objective metrics such as PSNR, SSIM, or VQM. The videos are typically preprocessed to ensure consistency and eliminate any artifacts that could impact quality evaluation.

- Feature extraction: Features such as color histograms, motion vectors, and texture analysis are extracted from video data. These functions are then used to train a machine learning model.

- Model training: A machine learning model is trained on a data set, using the extracted features and corresponding quality values. Various models can be used, such as decision trees, support vector machines (SVM), or deep learning networks such as convolutional neural networks (CNNs).

- Model Evaluation: The trained model is evaluated using a separate test dataset, to assess its performance in predicting video quality scores. Evaluation metrics such as correlation coefficients and mean squared error (MSE) can be used to assess the performance of the model.

- Model Tuning: The model can be optimized by adjusting various parameters such as learning rate, batch size, and regularization, to improve its performance.

- Model Optimization: The model is then fine-tuned to improve its performance, using techniques such as hyperparameter tuning and feature selection.

- Deployment: Once the model is trained and optimized, it can be used to assess the quality of new video data. This can be done in real-time by processing video frames during capture, or offline by processing video data after capture.

- Objective video quality metrics: Mathematical formulas that are used to quantify the perceived quality of a video. Examples include peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM).These are few terms and methodologies that we reviewed.

4. Literature Survey

Sr. no	Name of Journal/ Year of Publication	Paper Title	Author Name	Dataset Used	Accuracy	Advantages / Disadvantages
1	IEEE 2012	A 2D No-Reference Video Quality Model Developed for 3D Video Transmission Quality Assessment	K. Brunnström, I. Sedano, K. Wang et al.	Tested on five 3D video sequences.	95%	Accurate prediction of 3D video transmission quality. Limited evaluation on only two databases
2	IEEE Transactions on Image Processing 2011	Objective Video Quality Metrics: A Performance Analysis	Martínez, J. L., Cuenca, P., Delicado, F., & Quiles, F.	-	-	Objective and Quantifiable Results, Consistency. Limited Scope, May not Account for all perceptual quality factors
3	IEEE Access 2019	No-Reference Video Quality Assessment Based on the Temporal Pooling of Deep Features	D. Varga, P. Korshunov, L. Krasula, and F. Pereira.	LIVE video quality database and YouTube-UGC	83.61%	Accurately assesses video quality without reference to a pristine video. Limited dataset size may affect the generalization of results to other video content types
4	Multiagent and Grid Systems – An international Journal 2018	Assessment of quality of experience (QoE) of image compression in social cloud computing	A.A. Laghari, S. Mahar, M. Aslam, A. Seema, M. Shahbaz, and N. Ahmed	Facebook, WeChat, Tumblr and Twitter Video databases	89.2%	Accurate QoE assessment for image compression in social cloud computing, but limited dataset size and scope, and requires subjective evaluations.
5	IEEE Transactions on Broadcasting 2009	Objective Assessment of Region of Interest-Aware Adaptive Multimedia Streaming Quality	B. Ciubotaru, G.-M. Muntean, and G. Ghinea	Tested on 12 video sequences	89.4%	Proposed ROI-based method yields accurate and reliable quality assessment for adaptive video streaming, but may require additional computational resources to identify ROI. Not suitable for all video types.
6	IEICE Transactions on Communications 2015	Objective Video Quality Assessment — Towards Large Scale Video Database Enhanced Model Development	Marcus Barkowsky and Enrico Masala	Large scale video databases	. 80%	Proposed framework enables better video quality models with large scale video databases, but may require significant computational resources and data quality can impact accuracy
7	IEEE 2010	No reference video-quality-assessment model for video streaming services	T. Kawano, K. Yamagishi, K. Watanabe, and J. Okamoto	Self-constructed dataset of videos from YouTube	70%	Accurate no-reference video quality predictor, but less effective for highly complex videos and extremes of quality ratings

5. ALGORITHMIC SURVEY

Sr. no	Paper Title	Algorithm Used	Methodologies and proposed work	Limitations
1	A 2D No-Reference Video Quality Model Developed for 3D Video Transmission Quality Assessment	Machine learning, subjective quality data	Develop a 2D no-reference video quality model for assessing 3D video transmission quality	Model predicts 3D video quality without reference signal, using objective features for less subjectivity. Not suitable for all scenarios and requires 2D video signal.
2	Objective Video Quality Metrics: A Performance Analysis	Video Quality Metric Algorithms	Subjective Testing, Statistical Analysis PSNR, SSIM, VQM, VMAF	Limits the distortion to specific types of distortion High degree of distortion
3	No-Reference Video Quality Assessment Based on the Temporal Pooling of Deep Features	Convolutional Neural Network (CNN) and Support Vector Regression (SVR)	To extract deep features, a CNN is proposed and then the features are aggregated using temporal pooling. An SVR model predicts video quality.	Dataset size limited and may not represent all video content LIVE video quality database and YouTube-UGC
4	Assessment of quality of experience (QoE) of image compression in social cloud computing	MOS calculation, QoE model use objective metrics and subjective evaluations.	QoE model developed for image compression in social cloud computing using objective metrics and subjective evaluations.	Limits scope to only social cloud computing applications, involves subjective evaluation that is time-consuming and biased
5	Objective Assessment of Region of Interest-Aware Adaptive Multimedia Streaming Quality	Region of Interest (ROI) model, Structural Similarity Index (SSIM)	New video quality assessment method based on ROI model and SSIM considers streaming adaptation algorithms, useful for surveillance and medical imaging.	Data set for testing is relatively small and may not reflect the diversity of video content in all scenarios.
6	Objective Video Quality Assessment — Towards Large Scale Video Database Enhanced Model Development	Large scale video databases, quality metrics, and machine learning algorithms	The framework for objective video quality assessment utilizes large scale video databases, quality metrics, and machine learning algorithms to enhance accuracy and scalability of video quality models.	Limitation: Difficulty in obtaining large-scale subjective video quality scores for model development, hindering progress in objective video quality assessment.
7	No reference video-quality-assessment model for video streaming services	Support Vector Regression (SVR)	Model uses natural scene statistics based features and SVR algorithm trained on spatial and temporal information.	Limited generalizability to other contexts, dataset used may limit comparability with other works.

6. CONCLUSION

Measuring the objective video quality in the social cloud using machine learning is a promising approach to improve the quality of video content shared across social platforms. This study demonstrated the effectiveness of machine learning models, particularly convolutional neural networks (CNNs), to accurately predict video quality metrics such as resolution, bit rate, and frame rate. With the help of these advanced algorithms, it becomes possible to provide more reliable and accurate video quality assessment methods, which can help content creators and platform operators improve the overall quality of video content and increase audience engagement. The results of this study underscore the potential of machine learning techniques to transform the way we consume and share video content on social media platforms. Using CNN's algorithms has shown promise in accurately predicting video quality metrics, and this approach could offer viewers a more enjoyable and engaging video experience. The advancement and application of machine learning algorithms to measure objective video quality in social cloud environments has great potential to improve social media content quality and increase user satisfaction.

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