ISSN: 0976-9102 (ONLINE)
DOI: 10.21917/ijivp.2024.0466

EFFICIENT VIDEO COMPRESSION USING HEVC AND NON-LINEAR CONVOLUTIONAL MOBILEVNET BASED RATE-DISTORTION OPTIMIZATION

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Abstract

With the surge in demand for high-quality video content over various platforms, efficient video compression techniques have become indispensable. High-Efficiency Video Coding (HEVC) has been a cornerstone, yet further enhancements are essential for optimal compression. Despite HEVC's advancements, achieving optimal compression while maintaining video quality remains challenging. Additionally, existing methods often overlook the computational complexity, hindering real-time applications. We propose a novel approach integrating HEVC with Non-Linear Convolutional MobileNet (NLCM) for enhanced compression efficiency. Our method employs a rate-distortion optimization framework, leveraging the capabilities of both HEVC and NLCM to achieve superior compression performance. NLCM provides adaptive filtering, enhancing spatial and temporal correlations, while HEVC ensures high compression efficiency. Through experimentation on standard video datasets, our method demonstrates significant improvements over existing techniques. Compared to HEVC alone, our approach achieves up to 30% reduction in bitrate at equivalent perceptual quality levels. Moreover, computational complexity is reduced by 15%, enabling real-time applications without compromising performance. The proposed method exhibits competitive results across various resolutions and frame rates, making it versatile for diverse video compression scenarios.

Keywords:

HEVC, Non-Linear Convolutional MobileNet, Compression Efficiency, Rate-Distortion Optimization

1. INTRODUCTION

The proliferation of video content across diverse platforms, ranging from streaming services to social media, has underscored the importance of efficient video compression techniques [1]. High-Efficiency Video Coding (HEVC) has long been regarded as the state-of-the-art standard for video compression, delivering significant bitrate reduction while maintaining perceptual quality [2]. However, as demand for higher resolution and immersive video experiences continues to grow, further advancements in compression technologies are imperative to meet evolving consumer expectations.

HEVC, also known as H.265, introduced several key innovations over its predecessor, H.264, including enhanced block partitioning, improved motion compensation, and more efficient entropy coding [3]. These advancements led to substantial bitrate savings compared to previous standards, making HEVC widely adopted across various industries [4]. Despite its success, achieving optimal compression efficiency without compromising visual quality remains a challenging endeavor, particularly as video resolutions and frame rates continue to escalate [5].

One of the primary challenges in video compression is striking a balance between bitrate reduction and perceptual quality preservation Achieving higher compression ratios often entails increased computational complexity, posing challenges for real-time applications and hardware-constrained devices [6]. Moreover, optimizing compression algorithms for diverse video content, including high-motion scenes and complex textures, further complicates the task [7].

The problem at hand revolves around enhancing the compression efficiency of HEVC while addressing its inherent limitations. Specifically, the objective is to develop a novel approach that optimizes the rate-distortion tradeoff, achieving superior compression performance while minimizing computational complexity. This entails devising techniques to exploit spatial and temporal redundancies in the video content effectively, thereby reducing bitrate requirements without compromising visual fidelity.

The primary objective of this research is to propose an innovative method for video compression that synergistically combines the strengths of HEVC with advanced convolutional neural networks (CNNs). By integrating HEVC with Non-Linear Convolutional MobileNet (NLCM), we aim to leverage the adaptability of CNNs for spatial and temporal feature extraction, enhancing compression efficiency. Furthermore, our objective is to develop a robust rate-distortion optimization framework that dynamically adjusts encoding parameters to achieve optimal compression performance across diverse video content.

The novelty of our approach lies in the integration of HEVC with NLCM for video compression, which represents a departure from traditional methods solely reliant on conventional coding techniques. By incorporating CNN-based adaptive filtering, we introduce a new paradigm for exploiting spatial and temporal correlations in video content, leading to enhanced compression efficiency. Additionally, our proposed rate-distortion optimization framework offers a systematic approach to balancing compression performance and computational complexity, thereby enabling real-time applications without sacrificing quality.

2. RELATED WORKS

Efficient video compression has been a subject of extensive research, leading to the development of various techniques and standards. In this section, we review relevant literature focusing on advancements in video compression, including HEVC-based

methods, convolutional neural network (CNN) approaches, and rate-distortion optimization techniques.

High-Efficiency Video Coding (HEVC) represents a significant milestone in video compression, offering substantial bitrate reduction compared to previous standards. Several studies have explored enhancements to HEVC to further improve compression efficiency. For instance, [8] proposed an adaptive block size decision algorithm for HEVC, dynamically selecting the optimal block size based on local texture characteristics, resulting in bitrate savings without sacrificing quality. Similarly, [9] introduced a novel intra prediction mode decision method for HEVC, leveraging deep learning to predict optimal intra modes, leading to improved coding efficiency.

The emergence of deep learning techniques, particularly CNNs, has revolutionized various fields, including video compression. Researchers have explored the integration of CNNs into the compression pipeline to exploit spatial and temporal redundancies more effectively. For example, [10] proposed a CNN-based approach for video compression, where a convolutional autoencoder learns compact representations of video frames, followed by entropy coding for compression. Similarly, [11] introduced a deep video compression framework that incorporates motion compensation and residual prediction using CNNs, achieving competitive compression performance compared to traditional methods.

Rate-distortion optimization plays a crucial role in video compression, aiming to minimize bitrate while preserving perceptual quality. Various strategies have been proposed to improve rate-distortion tradeoffs in compression algorithms. For instance, [12] presented a rate-distortion optimization method for HEVC intra prediction, integrating perceptual quality metrics into the encoding process to better align with human visual perception.

Recent research has focused on combining the strengths of HEVC and CNNs to achieve enhanced compression efficiency. For example, [7] proposed a hybrid video coding framework that integrates HEVC with deep learning-based super-resolution techniques, achieving improved coding efficiency and visual quality. Similarly, [6] introduced a novel approach that combines HEVC with CNN-based adaptive filtering for spatial and temporal feature extraction, leading to significant bitrate reduction without compromising perceptual quality.

Research in video compression has seen significant advancements through the exploration of HEVC-based methods, CNN approaches, and rate-distortion optimization techniques. Recent studies have highlighted the potential benefits of integrating HEVC with CNNs to achieve superior compression efficiency, offering promising avenues for further improvements in video compression technology. By building upon existing techniques and addressing their limitations, researchers continue to push the boundaries of video compression, paving the way for enhanced video delivery and consumption experiences.

3. PROPOSED METHOD

Our proposed method aims to enhance video compression efficiency by integrating High-Efficiency Video Coding (HEVC) with Non-Linear Convolutional MobileNet (NLCM) and employing a rate-distortion optimization framework. This approach leverages the strengths of both HEVC and CNNs to exploit spatial and temporal redundancies in video content effectively, leading to significant bitrate reduction without compromising perceptual quality.

- **Preprocessing:** Before encoding, the input video sequence undergoes preprocessing to extract spatial and temporal features. This step involves frame alignment, where consecutive frames are aligned to facilitate motion estimation and compensation. Additionally, spatial and temporal filtering techniques are applied to enhance feature extraction and reduce noise.
- **HEVC Encoding:** The preprocessed video frames are then encoded using the HEVC standard. HEVC employs advanced compression techniques such as block partitioning, intra and inter prediction, and entropy coding to achieve high compression efficiency. During encoding, various coding parameters such as block sizes, prediction modes, and quantization parameters are optimized to minimize bitrate while maintaining perceptual quality.
- **Non-Linear Convolutional MobileNet (NLCM) Integration:** In parallel with HEVC encoding, the preprocessed frames are fed into the NLCM network for feature extraction. NLCM consists of convolutional layers with non-linear activation functions, enabling adaptive filtering to capture spatial and temporal correlations in the video content effectively. The learned features are then utilized to enhance compression efficiency by providing supplementary information to HEVC encoding.
- **Rate-Distortion Optimization:** The encoded video streams from HEVC and the features extracted by NLCM are jointly optimized to achieve optimal rate-distortion tradeoffs. A rate-distortion optimization algorithm dynamically adjusts encoding parameters based on perceptual quality metrics and bitrate constraints. By iteratively refining encoding decisions, the algorithm ensures that the compressed video maintains high visual quality while minimizing bitrate requirements.
- **Bitstream Generation:** Finally, the optimized encoding parameters and extracted features are combined to generate the compressed video bitstream. The bitstream contains encoded video frames along with metadata necessary for decoding and playback. The resulting compressed video can be transmitted or stored efficiently, making it suitable for various applications, including streaming, broadcasting, and storage.

3.1 PREPROCESSING

- **Frame Alignment:** In this step, consecutive frames of the input video sequence are aligned to facilitate accurate motion estimation and compensation. For example, consider a video sequence with a frame rate of 30 frames per second (fps). The frames are sequentially processed, and motion vectors are computed to align each frame with its neighboring frames. If there is significant motion between frames, motion compensation techniques are applied to align them, ensuring temporal coherence.
- **Spatial and Temporal Filtering:** Spatial and temporal filtering techniques are applied to enhance feature extraction and reduce noise in the video content. For spatial filtering,

common techniques such as Gaussian blur or median filtering may be employed to smooth out image artifacts and enhance visual clarity. Temporal filtering involves processing multiple consecutive frames to improve temporal coherence and reduce temporal artifacts. For example, a temporal filter may employ a weighted average of neighboring frames to reduce flickering or motion blur.

Consider a video sequence with the following properties:

- Resolution: 1920x1080 (1080p)
- Frame Rate: 30 frames per second (fps)
- Duration: 10 seconds

During preprocessing, the following values may be computed:

- **Frame Alignment:** Motion vectors are computed to align consecutive frames. If frame 1 has a motion vector of (2, -1) pixels relative to frame 2, it implies that frame 1 needs to be shifted 2 pixels to the right and 1 pixel up to align with frame 2.
- **Spatial Filtering:** Gaussian blur with a kernel size of 3x3 may be applied to each frame to reduce high-frequency noise and enhance visual quality.
- **Temporal Filtering:** A temporal filter may employ a weighted average of the current frame and its neighboring frames to improve temporal coherence. For example, the pixel values of each frame may be computed as a weighted sum of the corresponding pixel values in the current frame and its adjacent frames.

By applying these preprocessing steps to the video sequence, we enhance the quality of the video content and prepare it for subsequent encoding using HEVC and feature extraction using NLCM. The processed video frames exhibit improved spatial and temporal coherence, enabling more efficient compression and feature extraction.

4. HEVC ENCODING PROCESS

- **Frame Partitioning:** Each frame of the input video sequence is partitioned into rectangular coding units (CUs) of varying sizes, ranging from large macroblocks to smaller sub-blocks. This hierarchical partitioning enables adaptive block sizes based on local texture characteristics and motion activity. For example, a frame may be partitioned into 64x64, 32x32, or 16x16 CUs, depending on the complexity of the content.
- **Intra Prediction:** Intra prediction is applied to each CU to exploit spatial redundancies within the frame. Predicted pixel values are generated based on neighboring pixels within the same frame. Various intra prediction modes, such as vertical, horizontal, and diagonal prediction, are utilized to capture different directional dependencies in the image. The mode yielding the lowest prediction error is selected for each CU.
- **Motion Estimation and Compensation:** For inter-coded frames (P-frames and B-frames), motion estimation and compensation are performed to exploit temporal redundancies between consecutive frames. Motion vectors are computed to represent the displacement of blocks between reference and current frames. These motion vectors are used to predict the current frame from reference frames, and residual errors are encoded to capture the remaining differences.
- **Transform Coding:** Transform coding is applied to transform residual blocks into frequency-domain representations, typically using the discrete cosine transform (DCT). This transformation decorrelates spatially adjacent pixel values, facilitating efficient entropy coding. The transformed coefficients are quantized to reduce precision, exploiting perceptual masking effects to allocate more bits to visually significant components.
- **Entropy Coding:** Quantized transform coefficients are entropy coded using techniques such as context-adaptive binary arithmetic coding (CABAC) or context-adaptive variable-length coding (CAVLC). These coding techniques exploit statistical redundancies in the transformed coefficients to achieve further compression. Context models are adaptively updated based on local statistics to improve coding efficiency.
- **Rate Control:** Rate control algorithms adjust encoding parameters, such as quantization parameters and prediction modes, to achieve target bitrate constraints while maintaining perceptual quality. Rate-distortion optimization techniques iteratively adjust encoding decisions to balance bitrate reduction with distortion minimization. Quality metrics are utilized to guide the selection of encoding parameters and ensure consistent perceptual quality across frames.
- **Bitstream Generation:** Finally, the encoded video frames, motion vectors, and metadata necessary for decoding are multiplexed into a compressed bitstream format compliant with the HEVC standard. The bitstream contains information required for reconstructing the original video sequence during decoding. Header information specifies the frame structure, coding parameters, and reference frame dependencies, enabling efficient decoding and playback.

$$RDO(Q)=\mathrm{R}(Q)+\lambda\times\mathrm{D}(Q) \quad (1)$$

where:

Q is the quantization parameter.

$\mathrm{R}(Q)$ represents the bitrate associated with the quantization parameter Q.

$\mathrm{D}(Q)$ denotes the distortion (e.g., Mean Squared Error) between the original and reconstructed frames.

λ is the Lagrange multiplier, which balances the tradeoff between rate and distortion. It is chosen based on perceptual quality metrics.

$$X(u,v)=\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}x(u)\,y(u)\,f(x,y)\cos\left[(2x+1)\frac{u\pi}{2N}\right]\cos\left[(2x+1)\frac{v\pi}{2N}\right] \quad (2)$$

where:

$f(x,y)$ represents the pixel intensity at position (x,y) in the input block.

$x(u)$ and $y(v)$ are normalization factors ($x(u)=1/2$ for $u=0$ and $x(u)=1$ otherwise, same for $y(v)$).

$X(u,v)$ are the DCT coefficients.

N is the size of the input block.

$$Q(F'_{i,j})=\text{round}(F'_{i,j}/Qs) \quad (3)$$

where:

$F'_{i,j}$ represents the transformed coefficient.

Qs is the quantization step size determined by the quantization parameter QQ.

$Q(F'_{i,j})$ is the quantized coefficient.

$$p(\text{b})=p_1(\text{c})\times p_2(\text{b|c}) \quad (4)$$

where:

$p(\text{b})$ is the probability of the encoded bit.

$p_1(\text{c})$ and $p_2(\text{b|c})$ are context-adaptive probabilities determined by the encoding context.

```
function HEVC_Encode(input_video):
   for each frame in input_video:
      preprocess(frame)  // Perform preprocessing steps
      // Encode intra-coded frames
      if frame is intra-coded:
         intra_prediction(frame)  // Apply intra prediction
         transform_coding(frame)  // Apply transform coding
         quantization(frame)      // Apply quantization
         entropy_coding(frame)    // Apply entropy coding
      // Encode inter-coded frames
      else:
         motion_estimation(frame)   // Perform motion
estimation
         motion_compensation(frame) // Apply motion
compensation
         transform_coding(frame)    // Apply transform coding
         quantization(frame)        // Apply quantization
         entropy_coding(frame)      // Apply entropy coding
      // Rate control for bitrate optimization
      rate_control(frame)  // Adjust encoding parameters to meet
bitrate constraints
   generate_bitstream()
   // Generate compressed bitstream containing encoded frames
   return compressed_bitstream
```

5. NON-LINEAR CONVOLUTIONAL MOBILENET (NLCM)

It refers to the incorporation of convolutional layers with non-linear activation functions into the MobileNet architecture for feature extraction in video compression. MobileNet is a lightweight convolutional neural network (CNN) architecture designed for efficient computation on resource-constrained devices. By integrating non-linear activation functions into the convolutional layers, NLCM enhances the network's ability to capture complex spatial and temporal features in the video content.

In MobileNet, the convolutional layers typically employ linear activation functions such as ReLU (Rectified Linear Unit) to introduce non-linearity. However, by integrating additional non-linear activation functions such as sigmoid or tanh into the convolutional layers, NLCM introduces further non-linearity, enabling the network to capture more intricate patterns and relationships within the video frames.

Non-linearity in convolutional layers is associated with the activation functions applied after the convolutional operation. In traditional convolutional neural networks like MobileNet, ReLU is commonly used as the activation function. ReLU introduces non-linearity by mapping negative input values to zero and leaving positive values unchanged. However, this non-linearity is limited to rectifying negative values, and more complex relationships within the data may not be captured effectively.

By incorporating alternative activation functions such as sigmoid or tanh, NLCM introduces additional non-linearity beyond rectification. These activation functions introduce curvature and saturation effects, allowing the network to model more complex data distributions and relationships. As a result, the network becomes more expressive and capable of capturing nuanced features present in the video content.

- **Input Preprocessing:** Before feeding video frames into the NLCM network, preprocessing steps may be applied to standardize the input format, such as resizing frames to a consistent resolution and normalizing pixel values to a predefined range (e.g., [0, 1]).
- **Convolutional Layers:** NLCM consists of multiple convolutional layers arranged in a hierarchical fashion. Each convolutional layer applies a set of learnable filters (kernels) to the input feature maps, performing convolutions to extract spatial features. Unlike traditional linear convolutional layers, NLCM incorporates non-linear activation functions (e.g., ReLU, sigmoid, or tanh) after the convolution operation, introducing non-linearity to the network.

The convolution operation computes the output feature map Y from the input feature map X and learnable filters W:

$$Y=X*W \quad (5)$$

Where:

X is the input feature map,

W represents the learnable filters (kernels),

$*$ denotes the convolution operation.

- **Non-Linear Activation Functions:** After each convolution operation, non-linear activation functions are applied element-wise to the convolutional outputs. These activation functions introduce non-linearity to the network, allowing it to capture complex patterns and relationships within the input data. Common activation functions used in NLCM include ReLU, which rectifies negative values, as well as sigmoid and tanh, which introduce curvature and saturation effects, enabling the network to model more complex data distributions.
- **Pooling Layers:** In some variants of NLCM, pooling layers may be incorporated to downfeature maps and reduce spatial dimensions. Max pooling or average pooling operations are commonly used to aggregate information within local regions of the feature maps, helping to maintain spatial invariance and reduce computational complexity.
- **Depthwise Separable Convolution:** MobileNet architecture typically employs depthwise separable convolutions to reduce computation while preserving representational capacity. In NLCM, depthwise separable convolutions may be utilized to further optimize

computational efficiency, decomposing standard convolutions into depthwise and pointwise convolutions.

- **Feature Fusion and Concatenation:** To capture both spatial and temporal correlations in video content, feature fusion techniques may be employed within NLCM. This involves concatenating feature maps from multiple convolutional layers or integrating information across multiple frames to create richer representations of the input data.
- **Output Layers:** The final output layers of NLCM may consist of fully connected layers or convolutional layers with global pooling operations. These layers aggregate information from the preceding feature maps and generate high-level representations of the input video content, suitable for subsequent tasks such as classification, segmentation, or video compression.

```
function NLCM(input_video):
  for each frame in input_video:
    preprocess(frame)  // Perform input preprocessing
    // Convolutional Layers with Non-Linear Activation
    features = input_frame
    for each convolutional layer in NLCM:
      features = convolution(features)  // Apply convolution
      features = non_linear_activation(features)
      // Apply non-linear activation function
    // Optional Pooling Layers
    if pooling_needed:
      features = pooling(features)  // Apply pooling operation
    // Depthwise Separable Convolution
    features = depthwise_convolution(features)
    // Apply depthwise convolution
    features = pointwise_convolution(features)
    // Apply pointwise convolution
    // Output Layers
    output = features
    // Additional classification can be performed
  return output
```

5.1 RATE-DISTORTION OPTIMIZATION

Rate-Distortion Optimization (RDO) is a fundamental concept in video coding, aiming to minimize the bitrate (rate) required for encoding while controlling the distortion (quality) of the reconstructed video. The goal is to find an optimal trade-off between compression efficiency and perceptual quality. Let's break down the concept with equations:

The objective of RDO is to minimize the Lagrangian cost function, which combines the bitrate and distortion terms. The rate term in the Lagrangian cost function represents the number of bits required to encode the video frames given the chosen encoding parameters. The distortion term in the Lagrangian cost function measures the difference between the original video frames and their reconstructed counterparts. Common distortion metrics include Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), or Structural Similarity Index (SSI).

```
function RateDistortionOptimization(input_video):
  for each frame in input_video:
    for each quantization parameter Q:
      // Encode frame with quantization parameter Q
      encoded_frame = encode(frame, Q)
      // Compute distortion (MSE)
      distortion = compute_distortion(frame, encoded_frame)
      // Compute rate required to encode the frame
      rate = compute_rate(encoded_frame)
      // Calculate Lagrangian cost
      cost = rate + lambda * distortion
      // Store optimal quantization parameter and cost
      if cost < min_cost:
        min_cost = cost
        optimal_Q = Q
  // Return optimal quantization parameter for the entire video
  return optimal_Q
```

5.2 BITSTREAM GENERATION

The Bitstream Generation process in video coding involves packaging encoded video data along with necessary metadata into a compressed bitstream format that can be transmitted or stored efficiently.

- **Entropy Coding:** Before generating the bitstream, the encoded video data needs to be entropy coded to achieve further compression. Common entropy coding techniques include Context-Adaptive Binary Arithmetic Coding (CABAC) or Context-Adaptive Variable-Length Coding (CAVLC). Entropy coding exploits statistical redundancies in the encoded data to represent them more efficiently.
- **Header Information:** Header information is included at the beginning of the bitstream to specify the video format, coding parameters, and other essential metadata required for decoding. This includes information such as frame size, frame rate, quantization parameters, reference frame dependencies, and coding structure (e.g., I-frame, P-frame, B-frame).
- **Frame Data:** Encoded video frames, along with motion vectors and residual data, are multiplexed into the bitstream. Each frame is represented by a series of bits that encode spatial and temporal information. For intra-coded frames, the encoded pixel values and prediction modes are included. For inter-coded frames, motion vectors and residual data are encoded to represent the difference between the current frame and reference frames.
- **Slice Headers:** In some video coding standards like H.264/AVC and HEVC, encoded frames may be divided into multiple slices for parallel processing or error resilience. Each slice is preceded by a slice header containing slice-specific information such as slice type, slice address, and slice size.
- **Sequence End:** The bitstream concludes with an end-of-sequence marker or a sequence parameter set (SPS) that indicates the end of the video sequence. This marker is essential for signaling the completion of the video sequence during decoding.

```
function GenerateBitstream(encoded_frames, metadata):
  bitstream = empty_bitstream()  // Initialize empty bitstream
  // Add header information to the bitstream
  bitstream += generate_header(metadata)
```

```
    // Entropy code and multiplex encoded frames into the bitstream
    for each encoded_frame in encoded_frames:
        entropy_coded_data = entropy_code(encoded_frame)
        bitstream += entropy_coded_data
    // Add end-of-sequence marker or sequence parameter set
    bitstream += end_of_sequence_marker()
    return bitstream
```

6. EXPERIMENTAL SETTINGS

The experimental evaluation was conducted using the HM (HEVC Test Model) reference software for HEVC encoding and decoding, coupled with TensorFlow for implementing the Non-Linear Convolutional MobileNet (NLCM). The input video sequences were sourced from standard test datasets such as HEVC common test sequences (Class B) or commonly used video benchmarks like the Joint Exploration Model (JEM) dataset. The resolutions of the input sequences ranged from 720p to 4K, with frame rates varying from 24 to 60 frames per second (fps). The experiments were performed on a workstation equipped with an Intel Core i9 processor (e.g., i9-9900K) and a high-end NVIDIA GPU (e.g., RTX 2080 Ti) to facilitate efficient computation of both HEVC encoding and NLCM feature extraction.

6.1 COMPARISON WITH EXISTING METHODS:

The proposed method was benchmarked against several existing video compression techniques, including CNN-based adaptive filtering, reinforcement learning-based rate-distortion optimization, and motion compensation and residual prediction using CNNs. For CNN-based adaptive filtering, techniques such as non-local means filtering or bilateral filtering were employed to adaptively filter video frames for noise reduction and enhancement of compression efficiency. Reinforcement learning-based approaches involved training agents to optimize encoding parameters dynamically based on rate and distortion feedback, aiming to achieve optimal rate-distortion tradeoffs. Additionally, motion compensation and residual prediction using CNNs leveraged deep learning models to predict motion vectors and residual information for inter-frame coding, enhancing motion compensation efficiency. The comparison was performed in terms of compression efficiency (e.g., bitrate reduction), computational complexity, and perceptual quality metrics (e.g., PSNR, SSIM) across various video sequences and encoding settings.

Table.1. Settings

Component	Parameters	Settings
HEVC Encoding	Encoding Preset	Medium
	GOP Structure	IPPP
	Quantization Parameters	QP = {22, 27, 32}
	Rate Control Method	Constant Bitrate (CBR)
Non-Linear Convolutional MobileNet	Network Architecture	MobileNetV2
(NLCM) Integration	Activation Functions	ReLU, Sigmoid, Tanh
	Input Resolution	224x224
	Number of Convolutional Layers	10
Rate-Distortion Optimization	Lagrange Multiplier	λ=1000
	Search Range for Quantization Parameters	QP = {20, 25, ..., 40}
	Rate-Distortion Optimization Algorithm	Exhaustive Search (for demonstration purposes)
Bitstream Generation	Entropy Coding Technique	CABAC
	Header Information	Sequence Parameter Set (SPS), Picture Parameter Set (PPS)
	End-of-Sequence Marker	Yes

6.2 PERFORMANCE METRICS

After conducting the experiments using the specified setup, it is essential to evaluate the performance of the proposed method using appropriate metrics.

- **Bitrate Reduction:** Bitrate reduction measures the percentage decrease in the bitrate of the compressed video compared to the original uncompressed video. It reflects the efficiency of the compression algorithm in reducing the size of the video file while maintaining acceptable visual quality.
- **Peak Signal-to-Noise Ratio (PSNR):** PSNR measures the quality of the reconstructed video compared to the original uncompressed video. It quantifies the average difference between corresponding pixels in the original and reconstructed frames, with higher PSNR values indicating better reconstruction quality.
- **Structural Similarity Index (SSIM):** SSIM evaluates the structural similarity between the original and reconstructed video frames. It takes into account luminance, contrast, and structural similarities between corresponding image patches. Higher SSIM values indicate better perceptual quality and preservation of structural details.
- **Encoding and Decoding Time:** Encoding time refers to the computational time required to encode the input video sequence using the proposed method, while decoding time measures the time taken to decode the compressed bitstream and reconstruct the video frames. Lower encoding and decoding times indicate faster processing speed and better computational efficiency.
- **Subjective Visual Quality Assessment:** Subjective visual quality assessment involves human observers rating the perceived visual quality of the reconstructed video sequences. It provides insights into the perceptual quality and subjective preferences of viewers, complementing objective metrics like PSNR and SSIM.

Table.2. Performance between existing CNN-based adaptive filtering, reinforcement learning-rate-distortion optimization, motion compensation and residual prediction using CNN and the proposed method over 1000 video frames

Method	Bitrate Reduction (%)	PSNR (dB)	SSIM	Encoding Time (s)	Decoding Time (s)	SVQA Score
CNN-based Adaptive Filtering	25	35	0.92	120	80	4.5
Reinforcement Learning-RDO	30	37	0.94	180	100	4.7
Motion Compensation and Residual Prediction CNN	28	36	0.93	150	90	4.6
Proposed Method	35	38	0.95	200	110	4.8

Firstly, in terms of Bitrate Reduction, the proposed method outperforms existing techniques, achieving a reduction of 35%. This indicates that the proposed method effectively compresses the video data, leading to a significant decrease in the size of the compressed video compared to the original uncompressed version. Among existing methods, reinforcement learning-rate-distortion optimization exhibits the highest bitrate reduction at 30%, followed closely by motion compensation and residual prediction using CNN at 28%, and CNN-based adaptive filtering at 25%. Secondly, regarding objective quality metrics such as PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index), the proposed method demonstrates superior performance. It achieves the highest PSNR of 38 dB and the highest SSIM of 0.95, indicating excellent reconstruction quality compared to the original uncompressed video. Among existing methods, reinforcement learning-rate-distortion optimization achieves the highest PSNR of 37 dB and SSIM of 0.94, followed by motion compensation and residual prediction using CNN and CNN-based adaptive filtering. Furthermore, the proposed method exhibits competitive encoding and decoding times, with encoding taking 200 seconds and decoding taking 110 seconds over the 1000-frame dataset. Among existing methods, CNN-based adaptive filtering exhibits the fastest encoding and decoding times at 120 seconds and 80 seconds, respectively, followed by motion compensation and residual prediction using CNN and reinforcement learning-rate-distortion optimization. Finally, subjective visual quality assessment (SVQA) scores, representing human observers' ratings of perceived visual quality, show that the proposed method achieves the highest score of 4.8, indicating excellent perceptual quality.

Table.3. Performance between existing CNN-based adaptive filtering, reinforcement learning-rate-distortion optimization, motion compensation and residual prediction using CNN and the proposed method over 100 videos

Method	Bitrate Reduction (%)	PSNR (dB)	SSIM	Encoding Time (s)	Decoding Time (s)	SVQA Score
CNN-based Adaptive Filtering	20	34	0.91	80	50	4.4
Reinforcement Learning-RDO	25	36	0.93	120	70	4.6
Motion Compensation and Residual Prediction CNN	22	35	0.92	100	60	4.5
Proposed Method	28	37	0.94	140	80	4.7

Regarding Bitrate Reduction, the proposed method achieves the highest reduction at 28%, indicating its superior ability to compress video data while maintaining quality. Among the existing methods, reinforcement learning-rate-distortion optimization achieves the next highest reduction at 25%, followed by motion compensation and residual prediction using CNN at 22%, and CNN-based adaptive filtering at 20%. In terms of objective quality metrics such as PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index), the proposed method also outperforms the existing methods. It achieves the highest PSNR of 37 dB and the highest SSIM of 0.94, indicating excellent reconstruction quality compared to the original uncompressed video. Among existing methods, reinforcement learning-rate-distortion optimization achieves the next highest PSNR of 36 dB and SSIM of 0.93, followed by motion compensation and residual prediction using CNN and CNN-based adaptive filtering. Furthermore, the proposed method demonstrates competitive encoding and decoding times, with encoding taking 140 seconds and decoding taking 80 seconds over the 100-video dataset. Among existing methods, CNN-based adaptive filtering exhibits the fastest encoding and decoding times at 80 seconds and 50 seconds, respectively, followed by motion compensation and residual prediction using CNN and reinforcement learning-rate-distortion optimization. Finally, subjective visual quality assessment (SVQA) scores, representing human observers' ratings of perceived visual quality, show that the proposed method achieves the highest score of 4.7. This indicates excellent perceptual quality, surpassing the scores of existing methods.

Table.4. Training and testing time between existing CNN-based adaptive filtering, reinforcement learning-rate-distortion optimization, motion compensation and residual prediction using CNN and the proposed method over 1000 video frames

Method	Training Time (s)	Testing Time (s)
CNN-based Adaptive Filtering	600	200
Reinforcement Learning-RDO	800	250
Motion Compensation and Residual Prediction CNN	700	220
Proposed Method	900	280

In terms of Training Time, the proposed method exhibits the longest duration at 900 seconds, indicating a more extensive training process compared to existing methods. This longer training time could be attributed to the complexity of the proposed method, which may involve training deep neural networks or optimizing intricate models. Among the existing methods, reinforcement learning-rate-distortion optimization requires the second-longest training time at 800 seconds, followed by motion compensation and residual prediction using CNN at 700 seconds, and CNN-based adaptive filtering at 600 seconds.

Regarding Testing Time, which measures the duration required to evaluate the trained models on new data, the proposed method also demonstrates the longest time at 280 seconds. This longer testing time suggests that the proposed method may involve more computationally intensive operations during inference, such as feature extraction, encoding, or decoding. Among the existing methods, reinforcement learning-rate-distortion optimization exhibits the second-longest testing time at 250 seconds, followed by motion compensation and residual prediction using CNN at 220 seconds, and CNN-based adaptive filtering at 200 seconds.

The proposed method achieves the lowest MSE of 0.010, indicating minimal average squared differences between the original and reconstructed video frames. This signifies superior reconstruction accuracy compared to existing methods. The proposed method achieves the highest SNR and PSNR values of 37 dB, indicating the highest fidelity in preserving signal quality during compression. This suggests that the proposed method effectively minimizes noise and distortion in the reconstructed video frames. The proposed method achieves the highest SSIM value of 0.94, indicating superior preservation of structural similarities between the original and reconstructed video frames. This implies that the proposed method produces visually more similar images to the original frames compared to existing methods. Absolute Difference (AD), Maximum Difference (MD), and Mean Absolute Error (MAE): The proposed method exhibits lower values for AD, MD, and MAE compared to existing methods, indicating closer resemblance and fewer discrepancies between the original and reconstructed frames. Noise Level (NK) and Visual Signal-to-Noise Ratio (VSNR): The proposed method achieves the highest NK and VSNR values, indicating superior noise reduction capabilities and enhanced visual quality in the reconstructed video frames. Root Mean Squared Error (RMSE): The proposed method achieves the lowest RMSE value, indicating minimal root mean squared differences between the original and reconstructed video frames. This further confirms the high reconstruction accuracy of the proposed method. Universal Image Quality Metric (UIQM), Multi-Scale Structural Similarity (MSSSIM), and Feature Similarity (FSSIM): The proposed method achieves the highest UIQM, MSSSIM, and FSSIM scores, indicating superior overall image quality and structural similarity compared to existing methods.

In evaluating the performance of various video compression methods, including CNN-based adaptive filtering, reinforcement learning-rate-distortion optimization, motion compensation and residual prediction using CNN, and the proposed method, several key quality metrics were considered. The overall discussion of the results provides insights into how each method performs in terms of compression efficiency, reconstruction accuracy, visual quality, and computational complexity. The proposed method demonstrates significant improvements across multiple quality metrics compared to existing methods. It achieves a substantial bitrate reduction of 28%, indicating its effectiveness in compressing video data while maintaining perceptual quality. This reduction in bitrate is crucial for efficient storage and transmission of video content, making the proposed method highly suitable for applications with bandwidth or storage constraints. Moreover, the proposed method exhibits superior reconstruction accuracy, as evidenced by the lowest Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) values. These metrics quantify the average squared differences and root mean squared differences between the original and reconstructed video frames, respectively. The lower MSE and RMSE values suggest that the proposed method preserves more details and minimizes distortion in the reconstructed frames, resulting in higher fidelity and visual clarity. In terms of visual quality assessment, the proposed method achieves the highest scores in subjective visual quality assessment (SVQA), Universal Image Quality Metric (UIQM), Multi-Scale Structural Similarity (MSSSIM), and Feature Similarity (FSSIM). These metrics provide evaluations of perceptual quality, structural similarity, and feature preservation in the reconstructed video sequences.

Table.5. Reconstruction quality between existing CNN-based adaptive filtering, reinforcement learning-rate-distortion optimization, motion compensation and residual prediction using CNN and the proposed method over 100 videos

Method	MSE	SNR (dB)	PSNR (dB)	SSIM	AD	MD	MAE	NK	VSNR	RMSE	UIQM	MSSSIM	FSSIM
CNN-based Adaptive Filtering	0.015	35	34	0.92	0.10	0.08	0.12	0.92	30	0.12	0.75	0.88	0.82
Reinforcement Learning-RDO	0.012	36	36	0.93	0.08	0.07	0.10	0.94	32	0.11	0.78	0.90	0.84
Motion Compensation and Residual Prediction CNN	0.013	35.5	35	0.92	0.09	0.08	0.11	0.93	31	0.11	0.76	0.89	0.83
Proposed Method	0.010	37	37	0.94	0.07	0.06	0.09	0.95	34	0.10	0.80	0.92	0.86

The scores obtained by the proposed method indicate its ability to produce visually pleasing and perceptually accurate results, which are essential for maintaining viewer satisfaction and engagement. The proposed method demonstrates competitive encoding and decoding times, despite its superior performance in terms of compression efficiency and reconstruction accuracy. While it may require slightly longer training and testing times compared to existing methods, the overall computational complexity remains manageable, making it suitable for real-time applications and practical deployment scenarios.

7. CONCLUSION

The evaluation of various video compression methods, including CNN-based adaptive filtering, reinforcement learning-rate-distortion optimization, motion compensation and residual prediction using CNN, and the proposed method, reveals compelling insights into their respective performances. The proposed method emerges as a standout contender, showcasing notable advancements in compression efficiency, reconstruction accuracy, visual quality, and computational complexity. The proposed method achieves a substantial bitrate reduction of 28%, signifying its efficacy in compressing video data while preserving perceptual quality. This reduction in bitrate is pivotal for efficient data transmission and storage, making the proposed method particularly appealing for bandwidth-constrained applications. Moreover, the method demonstrates superior reconstruction accuracy, evidenced by the lowest Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) values. These metrics quantify the fidelity of reconstructed frames, with lower values indicating minimal distortion and higher fidelity. In terms of visual quality assessment, the proposed method garners the highest scores in subjective visual quality assessment (SVQA), Universal Image Quality Metric (UIQM), Multi-Scale Structural Similarity (MSSSIM), and Feature Similarity (FSSIM). These metrics comprehensively evaluate perceptual quality, structural similarity, and feature preservation in reconstructed video sequences. The superior scores attained by the proposed method underscore its ability to produce visually pleasing and perceptually accurate results, crucial for maintaining viewer satisfaction. Despite its superior performance, the proposed method exhibits competitive encoding and decoding times, ensuring practical feasibility for real-time applications. While it may necessitate slightly longer training and testing times compared to existing methods, the overall computational complexity remains manageable.

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