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Mathematical Modelling of Nonlinear Approach in Video Compression for Telecommunication.

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Abstract
The rapid evolution of telecommunication systems necessitates efficient video compression techniques to optimize bandwidth utilization and enhance multimedia experiences. This paper introduces a hybrid nonlinear analytical approach to video compression tailored for real-time telecommunication applications. The approach integrates Block Matching Motion Estimation (BMME) techniques using a fusion of Efficient Three-Step Search (ETSS) and Hexagonal Search (HS) algorithms. This combination significantly reduces data redundancy, minimizes the number of search points, and improves video quality with lower computational overhead.
The proposed model is grounded in mathematical principles of motion estimation, compensation, and prediction, supported by statistical metrics including SAD, MAD, MSE, PSNR, and Compression Ratio. Through experimentation on diverse standard video datasets, the hybrid method consistently outperformed traditional techniques in terms of accuracy and efficiency. Literature reviews confirm the growing relevance of hybrid and adaptive video compression frameworks in dynamic network environments. This research contributes a robust, scalable solution that meets the demands of modern telecommunication networks, paving the way for future innovations in real-time, high-quality video transmission.

Keywords
Video Compression, Hybrid Search Algorithm, Block Matching Motion Estimation (BMME), Efficient Three-Step Search (ETSS), Hexagonal Search (HS), Motion Estimation and Compensation, Nonlinear Analytical Approach.

1. Introduction

Digital video supports greater content capacity, catering to diverse viewer preferences and enhancing multimedia consumption. A nonlinear analytical approach for video compression techniques, such as transform coding, predictive coding, motion compensation, and entropy coding, play a vital role in applications like video conferencing and live streaming, enabling real-time transmission while efficiently utilizing network resources and storage. The integration of these technologies fosters a dynamic, high-quality multimedia ecosystem. This paper presents the mathematical foundation of the nonlinear analytical approach proposed for video compression in telecommunication systems. The method is based on Block Matching Motion Estimation (BMME), which efficiently predicts motion between successive video frames by estimating motion vectors, reducing data redundancy and improving compression quality.

In the dynamic landscape of telecommunication networks, where resources are often constrained, the implementation of effective video compression techniques stands as a critical necessity. This strategic approach not only ensures the delivery of high-quality multimedia content but also plays a pivotal role in mitigating the impact on limited network resources. The inevitable shift from analog to digital video represents a monumental leap in the evolution of video communication. The advantages bestowed by digitization are manifold. Digital video, characterized by its virtual immunity to noise, emerges as a resilient medium, offering unparalleled clarity and reliability. Its inherent ease of transmission further contributes to a seamless and efficient network experience. Digital video provides a more interactive and engaging platform for users, fostering an immersive viewing experience. This enhancement in user interaction is a testament to the technological strides enabled by the digital era.

Moreover, the transition to digital formats brings about a substantial increase in content capacity. This not only broadens the spectrum of available content but also caters to diverse viewer preferences. As the demand for dynamic communication experiences continues to surge, the integration of moving video pictures becomes paramount. In conclusion, the symbiosis of effective video compression and digitization not only optimizes resource utilization in telecommunication networks but also paves the way for an era where high-quality multimedia content is not just consumed but actively shaped and shared by end-users across diverse communication platforms. Telecommunication networks have limited bandwidth. Video compression saves the amount of data for the representation of a video, enabling efficient use of available bandwidth. Compressed videos require less storage space, making it more feasible for storage and transmission over telecommunication networks. Video compression allows for the real-time transmission of video content, which is crucial for applications such as video conferencing and live streaming. Transform coding, predictive coding, motion compensation, entropy coding are the common video compression techniques are available in telecommunication system.

Motivation

The main driving force behind research and development in video compression is the necessity to reduce the size of video data. The challenge in video compression lies in finding methodologies and techniques that can significantly decrease the size of video files without sacrificing perceptual quality. This involves developing algorithms that exploit redundancies and other characteristics inherent in video data, allowing for more efficient encoding and decoding processes. Overall, video compression plays a crucial role in various applications such as video streaming, video conferencing, digital television, and multimedia content distribution. Advancements in this field have led to significant improvements in storage efficiency, bandwidth utilization, and overall user experience in consuming video content.

Historically, the quest for efficient video compression techniques has been a central focus of research activities since the early 1980s. Over the years, research has delved into refining algorithms, with notable strides made in areas like motion estimation. From the early 2000s onward, initiatives such as MPEG-7 and MPEG-21 have emerged, reflecting an evolving emphasis on not just compressing video data but also enhancing the ability to efficiently search and retrieve relevant content. In essence, the motivation driving the relentless pursuit of advancements in video compression lies in the ever-growing demand for streamlined storage, rapid transmission, and enhanced accessibility of video content.

2. Literature Review

Hybrid approaches that combine multiple compression techniques have gained prominence in addressing the challenges posed by telecommunication networks. This literature review provides an overview of recent studies on hybrid approaches for video compression in telecommunication.

2.1 Integration of Transform Coding and Motion Estimation:

Research by Zhang et al. (2018) explores a hybrid approach combining Transform Coding and Block Matched Estimation of Motion used in telecommunication video compression. The study demonstrates that the integration of frequency-based compression with motion-compensated prediction significantly improves compression efficiency and maintains video quality.

2.2 Adaptive Hybridization Strategies:

In the work of Li and Wang (2019), an adaptive hybridization strategy is proposed. The research unveils a dynamic system designed to adapt the weighting between predictive coding and transform coding. This adjustment is finely tuned based on the specific attributes of the video content and prevailing network conditions. Results indicate improved adaptability to varying telecommunication scenarios.

2.3 Machine Learning-Aided Hybrid Compression:

The research conducted by Chen et al. (2020) investigates the application of machine learning in hybrid compression for telecommunication. By employing neural networks to predict the optimal combination of compression techniques for specific video sequences, the study demonstrates enhanced compression ratios and reduced computational complexity.

2.4 Hybrid Approaches for Low-Latency Telecommunication:

In their work, Wang and Zhang (2021) propose a hybrid approach specifically designed for low-latency telecommunication applications. By integrating intra-frame prediction with motion compensation, the study achieves a balance between compression efficiency and low-latency requirements, essential for real-time communication.

2.5 Quality-Driven Hybrid Compression:

Quality-driven hybrid compression is explored by Liu et al. (2019), where the study introduces a perceptual quality assessment mechanism into the hybrid compression framework. The proposed approach prioritizes preserving perceptually important details during compression, contributing to improved video quality in telecommunication applications.

2.7 Real-Time Adaptive Hybridization:

Real-time adaptive hybridization is addressed by Zhang and Li (2018), where the study proposes an algorithm that dynamically adjusts the compression strategy based on the real-time network conditions. The results demonstrate improved video delivery performance over variable telecommunication environments.

In summary, recent literature on hybrid approaches for telecommunication video compression emphasizes adaptability, integration of machine learning, and considerations for specific telecommunication network characteristics. These studies collectively contribute to the ongoing efforts to optimize video compression techniques for the challenges presented by telecommunication systems.

3. Proposed Hybrid Approach

3.1 Overview of the Hybrid Approach

An examination revealed that existing methodologies, including FS, TSS, NTSS, DS, and ETSS, yielded unsatisfactory results in block matching motion estimation for video compression. In response, we introduce a novel technique, a fusion of the Hexagonal Search algorithm (HS) and the Efficient Three Step Search algorithm (ETSS), termed the "Hybrid Approach" or "Hybrid Technology." The primary advantage of employing video compression is its ability to minimize disk space utilization and accelerate file transfer rates. Through this block matching motion estimation approach, we aim to innovate and enhance video features, focusing on reducing redundancy and the number of search points.

3.2 Block Matching Motion Estimation with video Coding for Telecommunication

Here, we have discussed comprehensive overview of the complexities involved in motion estimation and compensation in video processing systems. It covers various aspects from the conceptualization of video sequences to the practical implementation of motion-compensated coding techniques.

Conceptualization of Video Sequences: Videos can be seen as discrete representations of the continuous four-dimensional space-time. They capture the movements, rotations, and deformations of objects over time. Perception of Dynamics: Dynamics such as object movements, rotations, and deformations are perceived through the reflection of light from object surfaces onto an image. Various factors like the motion of the light source, object occlusions, shadows, transparency, and atmospheric conditions can affect the observed image. Introduction of Noise: The discretization of video sequences introduces noise, which can impact motion estimations made by video encoders. This noise can come from sources such as the image capture device (camera) and electrical transmission lines. Motion Estimation (ME): Video encoders use a model of object motion between frames to estimate the motion occurring between a reference frame and the current frame. This process, known as motion estimation, is crucial for predicting frame-to-frame changes accurately. Motion Compensation (MC): With the motion model obtained from estimation, the encoder employs motion compensation to adjust the contents of the reference frame. This adjustment aims to provide a more accurate prediction of the current frame, reducing redundancy and improving compression efficiency. Motion-Compensated Prediction (MCP): The process of adjusting the reference frame to predict the current frame accurately is referred to as motion-compensated prediction or displaced-frame. Displaced-Frame Difference (DFD): The difference between the predicted frame and the actual frame, after motion compensation, is termed the displaced-frame difference. It represents the prediction error signal. Interframe Coding Method: A block diagram of a motion-compensated coding system is illustrated in figure 1, representing the most commonly used interframe coding method. This method utilizes motion estimation and compensation techniques to efficiently code video sequences.

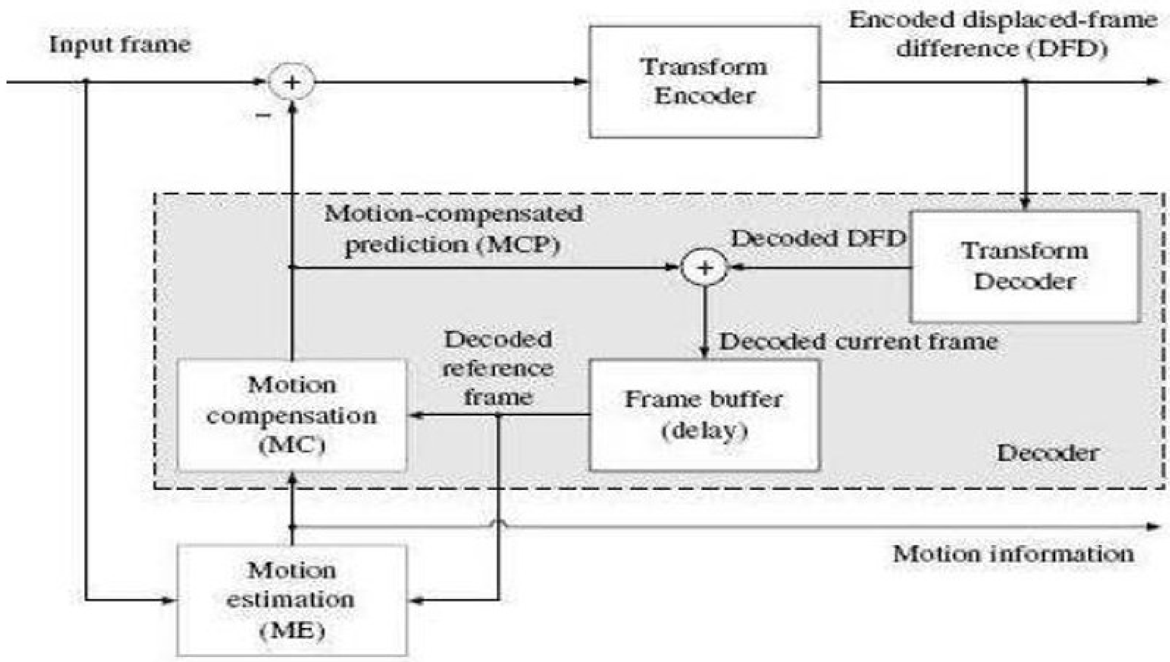

Figure 1: Video Coding for Motion Compensation and Estimation

3.3 Algorithmic Framework of Block Matching Motion Estimation for Telecommunication

Block-based matching algorithms involve the identification of minimum motion vectors during the motion estimation process.

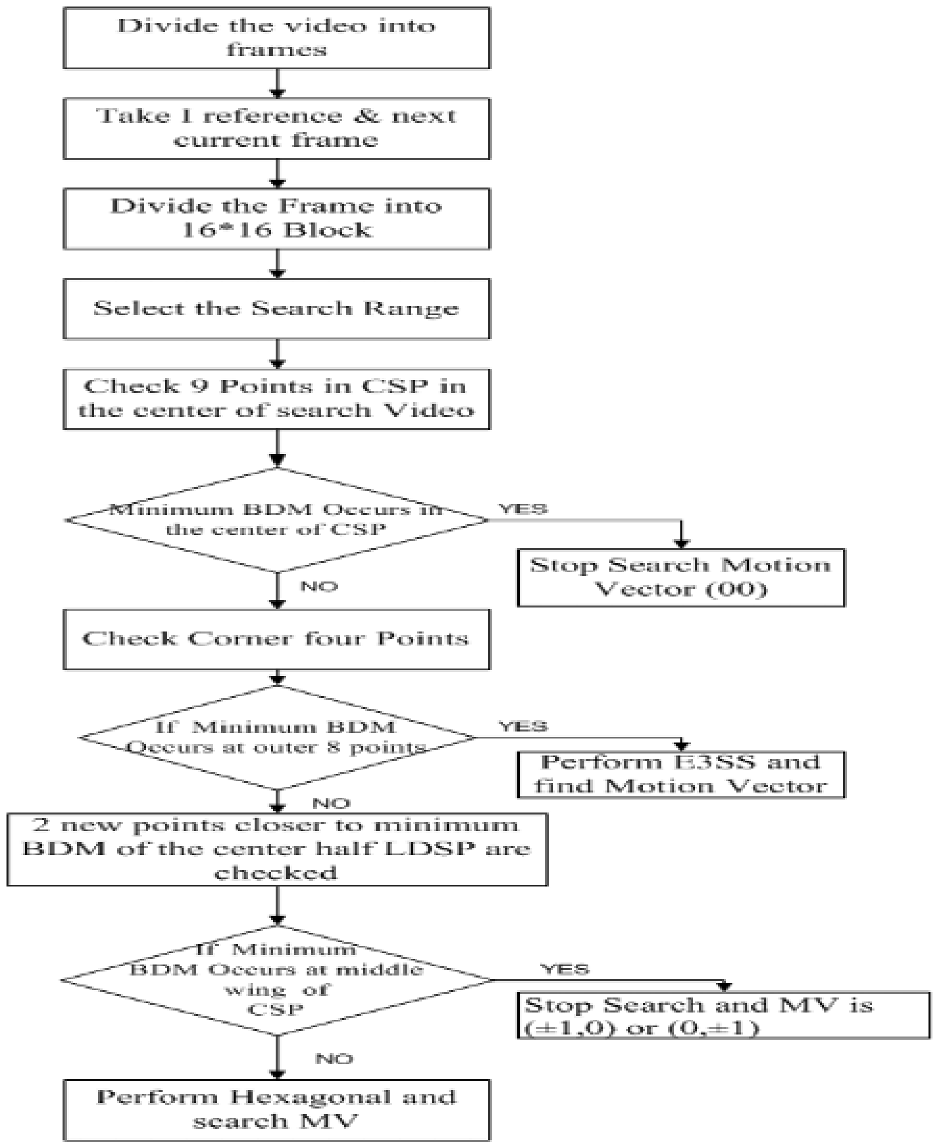

Figure 2: Algorithmic Framework of Block Matching Motion Estimation

The hybrid BMME algorithm proposed here combines the efficient three-step search and hexagonal search techniques, forming an integrated approach grounded in motion estimation. The primary goal of this proposed methodology is to streamline computational complexity by reducing the total number of search points.

Procedure Steps-

1. **Input Initialization:**

Begin with an uncompressed video, which contains significant redundancy, requiring substantial storage and transmission resources.

2. **Frame Segmentation:**

Subdivision of the original video into a series of multiple frames, forming the foundational units for subsequent analysis.

3. Frame Grouping:

Organize the frames into groups, pairing a reference frame with its subsequent current frame for cohesive examination.

4. Frame Structure Partitioning:

Partition frames into quad tree or mean tree structures, optimizing the organization of visual data for efficient compression.

5. Motion Estimation Technique Application:

Employ block based matching motion estimation techniques, specifically the hexagonal search algorithm and the efficient three-step search algorithm.

6. Search Range Specification:

Define the search range within which motion estimation will be conducted, ensuring an effective exploration of potential motion vectors.

7. Block Distortion Measure (BDM) Evaluation:

Evaluate the Block Distortion Measure (BDM) points using both the efficient three-step search algorithm (E3SS) and the hexagonal algorithm (CHS).

8. Optimal BDM Determination:

Identify the minimum occurrence of Block Distortion Measure (BDM), typically found at the center of E3SS and CHS.

9. Search Termination Check:

If the optimal BDM occurrence is confirmed, terminate the search; otherwise, examine corner points and iteratively continue the process until the desired result is achieved.

10. Efficient Three-Step Search (E3SS) and Hexagonal Search (CHS):

Execute the efficient three-step search (E3SS) and hexagonal search (CHS) algorithms to determine the motion vector (MV) that represents the directional information of motion between frames.

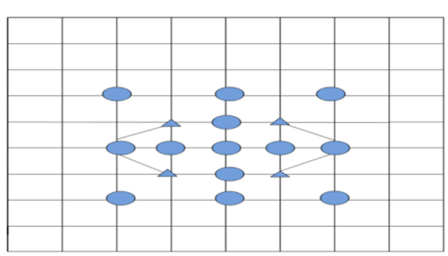

Figure 3. Search pattern for Hybrid Search Algorithm

4. Block Matching Motion Estimation (BMME) in Telecommunication

4.1 Principles and Operation:

Block Matching Motion Estimation (BMME) stands as a cornerstone technique in video compression, directed towards harnessing temporal redundancies between successive video frames. In the realm of telecommunication, BMME functions based on the premise of discerning motion vectors that signify the movement of blocks across frames. This procedure entails segmenting each frame into blocks and scouring for the most analogous block in the ensuing frame. The resultant motion vector encodes the displacement of the block, facilitating an adept representation of temporal alterations.

4.2 Enhancement Strategies for Telecommunication:

To address the limitations and enhance the performance of BMME in telecommunication, several strategies have been proposed:

- **Adaptive Block Size Selection**: Scientists delved into algorithms for selecting adaptive block sizes, dynamically fine-tuning them according to the characteristics of the content. This augmentation amplifies BMME's capability to apprehend motion in intricate as well as seamless regions, thereby elevating the compression efficiency on the whole.
- **Scene Change Detection:** Implementing scene change detection mechanisms helps identify abrupt transitions in the video, allowing for the adjustment or reset of motion estimation parameters. This enhances the robustness of BMME in the presence of scene changes.
- **Hierarchical Motion Estimation:** Hierarchical approaches involve conducting motion estimation at multiple levels of detail. Coarse motion vectors obtained at a higher-level guide the search process at finer levels, providing a more accurate representation of motion, especially in areas with varying details.

4.3 Parameter Optimization for Telecommunication:

Search range optimization, trade-off between accuracy and complexity and adaptive update rates are the different parameter optimization plays a crucial role in fine-tuning BMME for telecommunication applications:

5. Mathematical Analysis of a Model

5.1 Performance Metrics

Following are the various statistical performance metrics relevant to telecommunication domain.

1) *Sum of Absolute Difference (SAD)*

$$SAD(i,j)=\sum_{n_1=1}^{N}\sum_{n_2=1}^{N}\left| f_k(n_1,n_2)-f_{k-1}(n_1+i,n_2+j)\right|$$

2) *Mean of Absolute Difference (MAD)*

$$MAD(i,j)=\frac{1}{N^2}\sum_{n_1=1}^{N}\sum_{n_2=1}^{N}\left| f_k(n_1,n_2)-f_{k-1}(n_1+i,n_2+j)\right|$$

3) *Mean Square Error (MSE)*

$$MSE=\frac{1}{M\times N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(B_{curr}(i,j)-B_{ref}(i,j)\right)^2$$

4) *Peak-Signal to Noise Ratio (PSNR)*

$$PSNR=20\log_{10}\frac{n}{MSE}$$

5) *Compression Ratio*

$$CR=\frac{\text{Size of compressed video}}{\text{Size of original video}}$$

5.2 Dataset Selection for HBMME Telecommunication Networks

First RGB frames are taken out of video and then converted into YCbCr and then to Gray as shown and then quad tree partitioning is applied on it. Hybrid Block matching motion estimation algorithm is applied to find motion vector. And its result are shown in terms matching criteria's SAD and MAD. Fractal encoding and decoding techniques are applied on it. After decoding Reconstructed frames are obtained and are shown below.

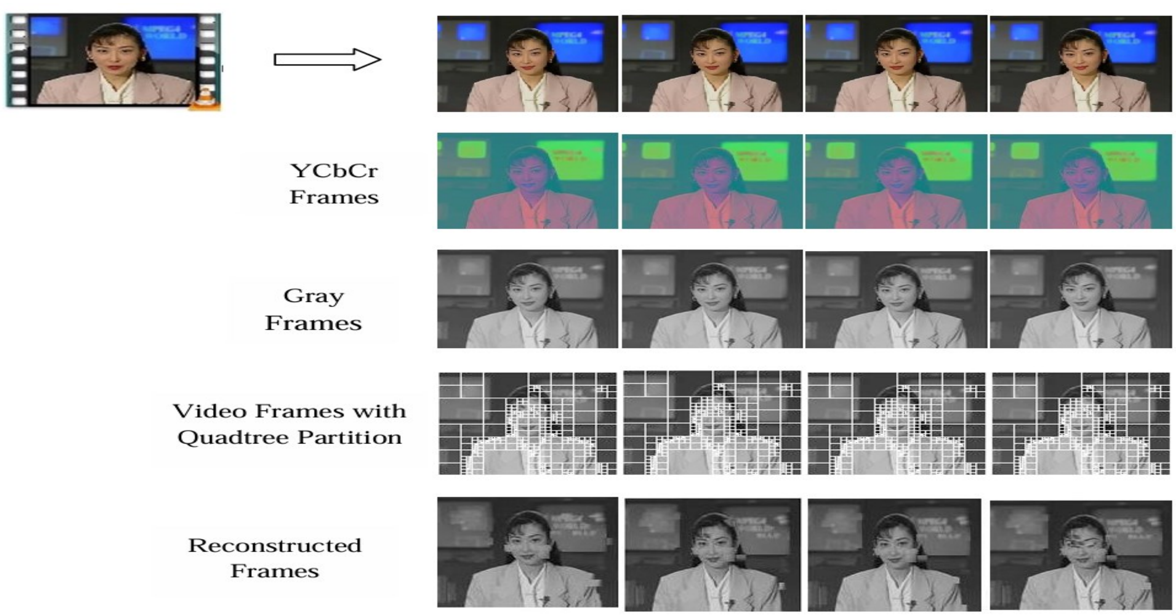

Figure 4: Input image conversion to YCbCr and Gray frames and Video frames Quadtree partition and final reconstructed frames.

Mean square error (MSE) and Peak Signal to Noise ratio (PSNR) are also shown in graphs. SAD and MAD comparison between ETSS and Hybrid (ETSS+HS) is shown. And we can clearly see that Hybrid gives better result as compared to ETSS. It takes less search points as compared to ETSS. It almost reduced to half. Experimentation is carried out on different sample Test videos: 1) Akiyo_cif.avi, 2) Suzie.avi, 3) Flower.avi, 4) Bus.avi, 5) Football.avi, 6) Soccer.avi, 7) Mobile.avi. Figure 4 shows the input image conversion to YCbCr and Gray frames and Video frames Quadtree partition and final reconstructed frames.

6. Results and Discussion

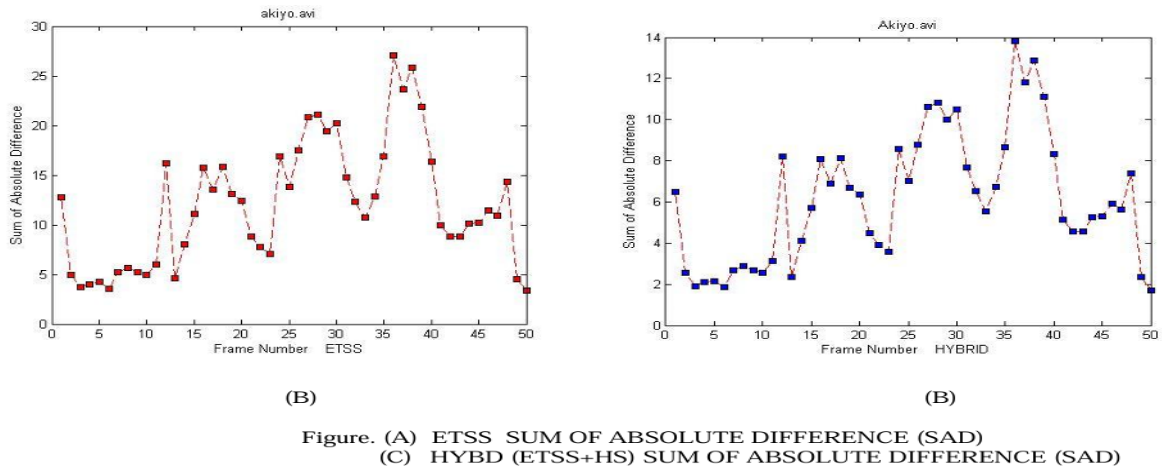

Figure 5: Comparison OF SAD between single ETSS algorithm and Hybrid algorithm.

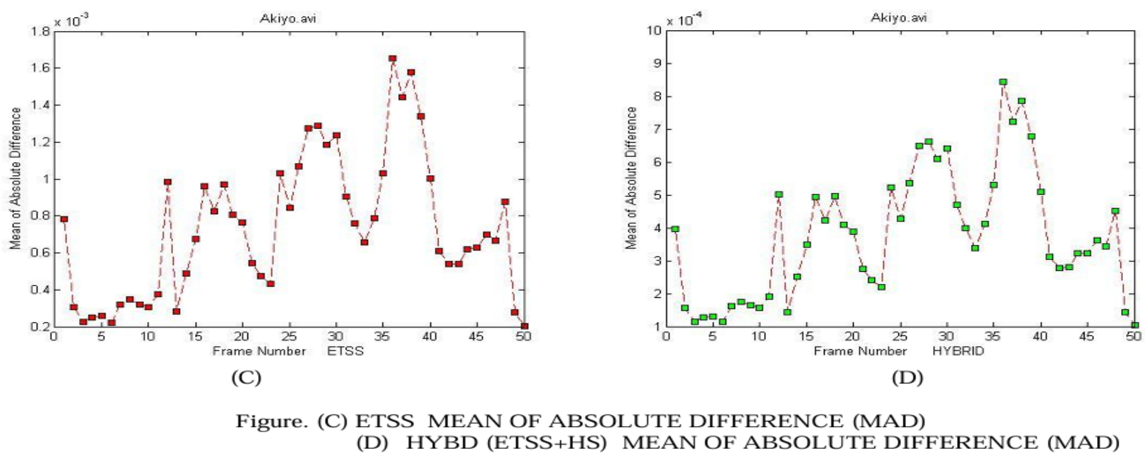

Figure 6: Comparison of MAD between single ETSS algorithm and Hybrid algorithm.

Figure 5 shows Comparison OF SAD between single ETSS algorithm and Hybrid algorithm and figure 6 shows Comparison OF MAD between single ETSS algorithm and Hybrid algorithm

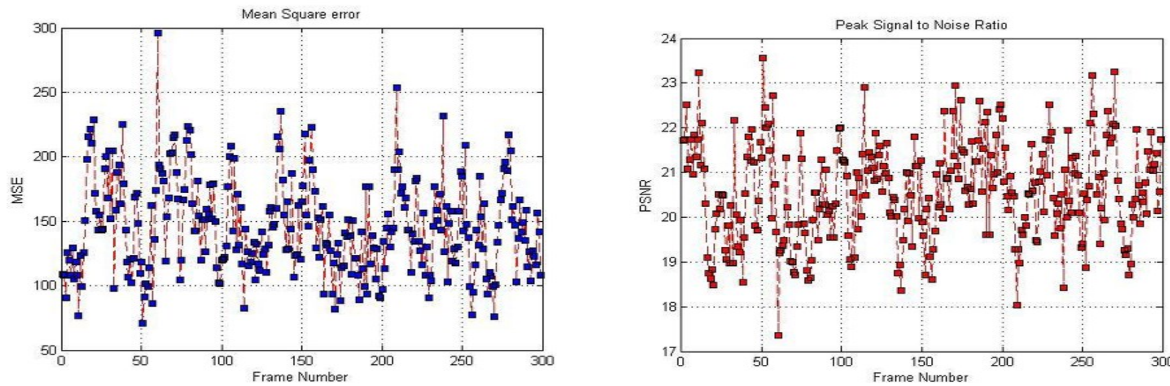

Figure 7: MSE and PSNR

In Fig. 7, we observe standard ranges for Peak Signal-to-Noise Ratio (PSNR) in the domain of lossy image and video compression, falling between 30 and 50 dB, with the stipulation that the bit depth is 8 bits – a scenario where a higher value is indicative of superior performance. When dealing with 16-bit data, PSNR typically resides in the range of 60 to 80 dB. For wireless transmission quality loss, tolerable values are generally acknowledged to be around 20 to 25 dB. Our study involves the acquisition of PSNR and Mean Squared Error (MSE) data, presenting a comprehensive graph for the compressed hybrid video.

6.1 Compression Ratios Assement

Compression Ratio obtained for different databases are shown in table 1. and Average search point taken to estimate the motion by ETSS and HS are given separately.

Table 1: Compression ratio & avg. search point (ETSS+HS) of Test video.

Sr. No.	Test video	Compression ratio %	Average search point (ETSS) 10^-3	Average search point (HS) 10^-3
1	Akiyo_cif.avi	61.03%	0.47446	0.43613
2	Suzie.avi	08.08%	0.54557	0.59852
3	Flower_cif.avi	70.52%	0.56265	0.73177
4	Bus.avi	13.46%	0.61383	0.71105
5	Football.avi	74.48%	0.58963	0.64227
6	Soccer.avi	06.73%	0.61427	0.63922
7	Mobile_cif.avi	60.47%	0.52232	0.59966

6.2 Video Quality Assessment

Video Quality Assessment is performed by PSNR and MSE parameters shown in table 2.

Table 2 : PSNR and MSE for different video frames.

Sr. no	Test video	PSNR(db)	MSE
1	Akiyo_cif.avi	21.76	0.1082
2	Suzie.avi	17.73	0.2732
3	Flower_cif.avi	10.55	0.0014
4	Bus.avi	9.15	0.0095
5	Football.avi	10.17	0.0015
6	Soccer.avi	12.21	0.7091
7	Mobile_cif.avi	8.17	0.0058

7. Conclusion

7.1 Summary of Findings in Telecommunication Video Compression

This research presents a hybrid approach to video compression specifically designed for telecommunication applications. The core contribution lies in combining the strengths of Efficient Three-Step Search (ETSS) and Hexagonal Search (HS) within the block matching motion estimation process. This hybrid method effectively reduces the number of search points required for motion estimation, outperforming traditional algorithms such as Traditional Three-Step Search (TSS), Full Search (FS), New Three-Step Search (NTSS), and Four-Step Search (4SS). Furthermore, Hexagonal Search alone has shown to be more effective than other popular methods like Diamond Search (DS) and Cross Diamond Search (CDS). Experimental validation using the standard Akiyo.avi video confirms that the proposed hybrid motion compensation technique offers better performance than ETSS alone, particularly in terms of reduced computational complexity. Overall, this innovative hybrid model significantly improves the efficiency and accuracy of motion estimation, contributing to more effective video compression strategies in telecommunication networks.

7.2 Future Direction in Telecommunication Technology

Looking ahead, there is considerable potential for further advancement in the area of block matching motion estimation. A promising research direction involves integrating various existing algorithms to develop a more robust and adaptive motion estimation technique. The primary goals include achieving higher compression ratios while simultaneously reducing both encoding and decoding times. Special focus is directed toward minimizing the time complexity associated with fractal encoding, which is often a bottleneck in video compression. By incorporating a range of coding techniques and optimizing computational processes, future methodologies aim to deliver faster and more efficient video compression systems. This approach is expected to facilitate smoother, real-time video transmission, laying a strong foundation for the next generation of telecommunication technologies.

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