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LINKED MOTION ESTIMATION METHOD BASED FEATURE VECTOR WITH PSO INTEGRATED MEAN SHIFT TECHNIQUE FOR VIDEO STEGANOGRAPHY

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ABSTRACT

Video steganography is the practice of concealing a message in a video file in order to transmit it invisibly. For secure online and all communication, the ability to use digital steganography to hide communications is essential. Security applications rely on steganography, which is embedded in video frames and films, to protect sensitive information. In order to reduce data transit and storage requirements, most social media networks use lossy video transcoding. Most video steganography systems cannot be used for secure social media-based communication due to the process of video transcoding. In order to establish dependable secret communication on social media platforms, a robust video steganography model is proposed using the extracted featured from the video to counteract the effects of video transcoding. This research presents a novel method for object-based video steganography, which involves encoding secret data into the motion vectors of objects in motion. Consequently, the objects present in each frame are identified using the mean shift technique. The Motion Vector (MV) of every item is restored to within a quarter of a pixel using a method that estimates motion from B and P frames. Determining the ideal storage-to-video-quality ratio for the chosen motion vectors and associating them with the object requires defining a threshold value. For this reason, we only take into account the motion vectors whose values exceed the threshold. By comparing the magnitude that has been achieved to the threshold value, an action vector is chosen that is larger than the threshold value. For any moving object, the correct vectors are always chosen. Hence, the small motion vectors that didn't come from a geographically significant area are removed. The hidden information is encoded in a quarter of the horizontal and vertical components of the motion vectors that are being tracked. The proposed model makes use of Particle Swarm Optimization (PSO) for updating the feature set for accurate motion detection. In this research a Linked Motion Estimate Method with PSO Integrated Mean Shift Technique using the Weighted Feature Vector (LMEM-PSO-MST-WFV) is proposed for video steganography for secure transmission. The statistics useful for steganography may be affected by changes made to the motion vector during the information embedding process. The proposed model performance in region of motion based feature vector for video steganography is compared with the traditional model and the results represent that the proposed model performance is high.

Keywords: *Video Steganography, Lossy Video Transcoding, Motion Estimate Method, Mean Shift Technique, Feature Vector, Secure Transmission.*

1. INTRODUCTION

Understanding steganography allows for a secret line of communication between transceivers. Steganography is the practice of disguising sensitive data within a seemingly innocuous file [1]. As the reach of the internet has grown, digital multimedia files have become a common means of exchanging a wide range of information [2]. These documents, which can include text, audio, image, and video, offer a protected environment for the transmission of data [3]. There are also methods for hiding secret data, and research into a field called steganalysis [4] that can decipher encrypted

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messages is ongoing. Numerous studies have focused on the images or videos because it is one of the most widely used forms of media nowadays. However, it is restricted when transferring a significant amount of data due to its low capability in disguising the data [5]. Multiple video frames and their formation into a single large frame both contribute to the great signal space capacity that this solution offers [6]. As the hidden message is inserted between frames, it is difficult for a picture steganography program [7] to find it.
Mean-shift algorithm is one of the most well-known of the strategies since it is faster than most other tracking methods [8] and can be easily integrated into real-time systems [9]. Large magnitude values in motion vectors aren't always indicative of actual motion. Therefore, only motion vectors of regions where the moving objects are present are retrieved [10], rather than the amplitude of motion vectors for the entire image being measured [11]. These regions are identified with high precision with an object tracking system [12]. A novel algorithm for video steganography is presented in this research. The proposed methodology incorporates techniques from both motion estimation and steganography in order to decipher the secret information hidden within the motion vectors of passing objects [13].
The statistical features of a motion vector are lost in these processes, making them vulnerable to statistical steganography detection techniques [13]. Message embedding accuracy is improved by second-generation approaches, which also define the appropriate distortion function [14]. The core idea behind these techniques is to create a distortion function that adequately describes how embedding affects motion vectors [15]. Second-generation approaches are based on the idea that a greater number of hidden message bits can be embedded [16] to alter one of the motion vectors, hence reducing the distortion for a given payload [17]. When using a third-generation technique, it is common to redirect the motion vector to regions where some absolute differences (SAD) are locally optimal [18]. This method ensures that the optimality of the motion vector is maintained by always choosing the local optimal motion vector in the region, which corresponds to the message [19]. When the bit rate or message length is low, detection of the methods as such is challenging [20]. No assurance can be given by these algorithms that the motion vector will be redirected to a better position [21]. Consequently, these strategies can be uncovered if the local optimal estimator is executed with more accuracy [22].
Video steganography has long used techniques like least significant bit (LSB) substitution to implant secret messages into video frames, which alters the values of the pixels' least significant bits [23]. This approach is highly regarded for its ability to conceal information effectively while preserving the video's visual quality. LSB is an essential algorithm that explains the inner workings of more advanced methods. The LSB approach has been the most popular video steganography technique due to its efficient data embedding capabilities and ease of implementation. Furthermore, there are alternatives that improve embedding robustness and data security, such as TPV and BPCS. These techniques add to the knowledge of video steganography algorithms as a whole.

If users want the best possible steganographic output, they must include loss functions while embedding. Cover frame reconstruction loss (Lc) is a popular loss function that measures how different the original and changed frames are. To further guarantee that the model successfully minimizes the variance between the steganographic frames and their associated cover frames, weighted L2 loss functions are also utilized [24]. The existing types of data hiding techniques can be expanded by integrating LSB approaches into more complicated methods, such as those that use Discrete Wavelet Transform (DWT) for efficient data embedding within video streams. It is clear that video steganography has a lot of promise and adaptability due to the variety of embedding techniques available.
Steganography can be used in video files to conceal data and send it to an unintended recipient. Because of the widespread use of video content, its compression is crucial. Since video data consume more capacity, compression is essential before encrypting, transmitting, storing, or uploading the video to the internet. First, there is lossy compression, and second, there is lossless compression. For smaller versions of previously enormous files, compression is a useful tool. After some preliminary processing, video compression should be applied [25]. Two of the most important parts of the preprocessing phase are improving video quality and efficiency and removing noise from the data [26]. Applying a median filter allows users to obtain high-quality data with minimum noise. Encoding and decoding data is a breeze, and you'll be pleased with the outcomes. An essential component of the motion estimate process is the motion vector. Using the position of the same or a comparable macro block in another image, it is

possible to generate an image representation of the macro block.
Motion vector is a method for feeding data from the momentary state of a live video stream using the LSB methodology [27]. The term motion vector refers to data about motion that is either real-time or lagged behind the frame. Due to the absence of a third party, confidentiality of the data is ensured [28]. The motion vector mostly focuses on the macro model and patchwork. Patches are like the tiniest pieces of pixel architecture. In order to determine the motion vectors for each video frame, we use the magnitude value of the current frame as a reference and the pixel-by-pixel variation of the macro model with respect to the motions. With the use of video steganography, a secure channel can be set up by hiding a message inside the visual data itself. The motion estimation process is shown in Figure 1.

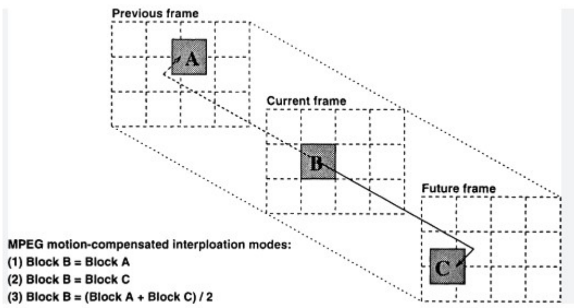

Fig 1: Motion Estimation Process

In this research, a new approach for video steganography motion vector using mean shift technique is proposed, in which hidden information is concealed inside the vectors of motion of moving objects. For this reason, the mean shift algorithm is used to identify the items that are present in each frame. Each object's motion vectors are retrieved to an accuracy of a quarter of a pixel based on a motion estimate method. The motion estimation complete process is depicted in Figure 2.

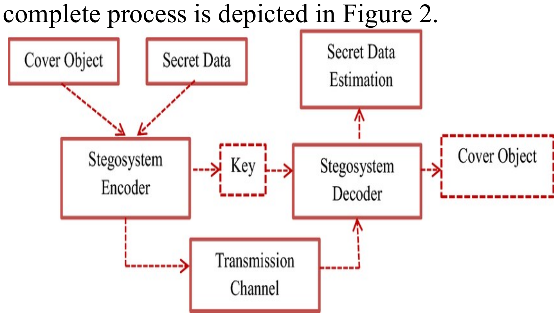

Fig 2: Complete Process of General Motion Estimation for Steganography [15]

To guarantee that the chosen motion vectors are indeed associated with the object in question and to strike the optimal balance between storage requirements and video quality, a limit is specified. Thus, the motion vectors with values higher than the threshold are chosen. In this research a Linked Motion Estimate Method with PSO Integrated Mean Shift Technique using the Weighted Feature Vector is proposed for video steganography for secure transmission. Initially the frames are extracted from video and pixel extraction is performed. The motion estimation is applied and finally steganography is applied to provide security.

By increasing data capacity while preserving perceptual quality, existing methods including Least Significant Bit (LSB) substitution, Transform-Domain embedding, and MV-based approaches have made contributions to the subject. Unfortunately, they have a lot of processing cost, aren't very resilient against compression artifacts, and aren't very adaptable to motion dynamics. For instance, steganalysis techniques can quickly detect traditional LSB-based approaches despite their simplicity and high embedding rates. In a similar vein, models that rely on motion vectors to enhance concealment in dynamic frames are prone to unstable detection and retrieval accuracy due to their disregard of object borders and global motion changes. While current methods based on distortion and feature consistency work well in static settings, they aren't well suited to situations involving dynamic or real-time video transmission, when motion irregularities and frame correlation change constantly.

In response to these limitations, a more resilient and adaptable approach to video steganography was developed in the form of a framework: LMEM-PSO-MST-WFV. The system improves the accuracy of motion vectors and inserts data into contextually important areas of video frames by integrating motion estimates, feature-based weighting, and PSO-driven optimization. For accurate object detection and tracking, use the Mean Shift algorithm. For maximum embedding security and minimum distortion, use PSO optimization, which dynamically changes feature weights. Improved resilience against transcoding effects, preservation of video integrity, and excellent steganographic accuracy even in compressed or real-time situations are all results of this integrated design, which aims to rectify the flaws of previous techniques. Therefore, the suggested architecture helps lay a smarter and more trustworthy groundwork for safe multimedia communication.

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The section 1 describes briefly about the requirement of Steganography, motion vectors and optimization technique for applying video steganography. Section 2 presents a brief literature review on the traditional Steganography models. Section 3 clearly explains the Linked Motion Estimate Method with PSO Integrated Mean Shift Technique using the Weighted Feature Vector generation process. Section 4 provides the comparative analysis of the proposed model with the traditional models and the results are visualized. Section 5 concludes the paper.

2. LITERATURE REVIEW

Liu et al. [1] introduced a novel MV steganographic approach for H.264 video that can greatly enhance security performance in the face of the recently developed, potent multi-domain feature set motion vector consistency (MVC). The suggested distortion function, denoted by the notation dMVC, takes into account both the MV statistics and the degree of consistency of motion vectors for sub-blocks within a macroblock (MB) or sub-macroblock (sub-MB). In addition to showing that the proposed dMVC may be integrated with current approaches, the author showed that it can withstand joint steganalytic attacks on the MVC feature and local optimality features, such as NPELO, inside the minimal distortion embedding framework.

The effectiveness and security of video steganography's encoding process depend on the assignment of fees. Existing cost assignment algorithms for adaptive video steganography are only suitable for a subset of the possible transform coefficients. In addition, the existing video steganographic frameworks do not allow Syndrome-Trellis Codes (STCs) to simultaneously modify all transform coefficients in intra-coded and inter-coded frames. To get over these limitations, Chen et al. [2] proposed a new architecture for video steganography. Disturbance drift in intra- and inter-coding processes was lastly theoretically investigated by the author. With these details, the author created the DDCA method, which stands for Distortion Drift-Based Cost Assignment. Two separate video datasets were used to conduct extensive testing on the proposed video steganographic architecture and DDCA to determine its performance and security.

In order to address the irreversibility problem that has affected numerous well-known neural network models for hidden data extraction, Peng et al. [3] propose a new image steganography framework that uses a gradient descent approximation and a Generative Adversarial Network (GAN) generator. The first step in making a stego image is to use a predefined mapping rule to insert the secret data into a stego noise vector. In order to extract data, the noise vector is incrementally updated using gradient descent with the generator. The updated noise vector will approach the stego noise vector, and the generator's output image will resemble the stego image if the error is decreased to within the tolerance range. At last, we get to extract the secret data from the updated noise vector. Results in terms of extraction accuracy, throughput, and robustness are all satisfactorily produced by the analyses and trials carried out utilizing WGAN-GP (Wasserstein GAN-Gradient Penalty).

Because digital video offers a great deal of leeway in terms of embedding domains, video steganography can take many different forms. Nevertheless, the current video steganalytic traits are domain-specific, which makes it challenging to identify steganography in a wide variety of embedding contexts. A consistent collection of features for detecting video steganography in various contexts was proposed by Zhai et al. [4] in this study. The author considered the well-known PM domain and the MV domain for steganography. The idea is based on the observation that, within a particular macroblock, sub-block MVs normally vary from one another, but generally tend to converge on a common set of values following MV or PM changes.

Existing video steganography methods, which employ either the decoded frame images or the compression coding parameters, can lead to a degradation in the quality of the rebuilt frames. Liu et al. [5] used the state-of-the-art motion vector prediction (AMVP) algorithm in the HEVC standard to offer a lossless adaptive steganographic approach for H.265/HEVC films. For embedding, we employ the index value of the prediction unit (PU) from its candidate list. When tested experimentally, the proposed steganographic approach proved to be more effective than steganalytic detectors based on either feature analysis or deep learning networks. An uncharted embedding space was explored in this paper.

Inter prediction methods carried out by hybrid video codecs rely heavily on block-based motion estimation. In order to calculate block MVs, the most popular approaches rely on time-consuming and resource-hungry search processes based on matching blocks. The aperture problem is another issue with these blocks, and it tends to get worse as the block size gets smaller. Furthermore, common

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codecs' block matching criteria disregard the perceptual quality of the motion compensated images produced after decoding. In an effort to reach the nebulous goal of perceptually optimised motion estimation, Paul et al. [6] proposed a search-free block motion estimation framework that employs a multi-stage convolutional neural network and can perform motion estimation on multiple block sizes simultaneously by taking in a trio of frames.

Because of the time needed to load and watch each video, finding the appropriate movie in a large collection is more difficult than searching for relevant images. The majority of video-sharing and -streaming websites provide a preview of the material to enhance the user experience while surfing. This is where Zhu et al. [8] tried to make a video teaser out of a still image. With this in mind, the author proposed a cascaded pair of networks: one for motion embedding and one for motion expansion. An integrated picture or video snapshot containing both geographical and temporal data is the end aim of the motion embedding network. The motion expansion network is introduced to revers the video from the input video snapshot. In order to train the network to focus on temporal information while preserving the invertibility of motion embedding and expansion, the author created a motion attention module and four unique losses. Extensive testing confirms that this method effectively merges a video's spatio-temporal data into a single live picture, which can subsequently be transformed into a video preview.

3. PROPOSED MODEL

Steganography entails concealing private data within a video or audio recording so that it cannot be accessed by unauthorized parties. Both cryptography and steganography employ a similar methodology to hide critical information, which can be confusing to hackers trying to break into the encrypted data. In spite of this, steganography is an effective method since the data are encrypted even without recipient's knowledge.

The video stream consists of three main types of frames: I-frames, which are completely self-referential and use intra-prediction, P-frames, also called predicted frames, and B-frames, which are bidirectional P-frames. Intra-prediction is used to create a DCT data stream from the encoded I-frame, while motion estimation is used to create motion vectors from the encoded P and B frames. Micro blocks are smaller units in both B and P frames. The goal of this research is to conceal a message in the trajectory of fast-moving vectors, as previously mentioned. It's possible that this property is not included in the embedded information of any motion vectors generated from the bounding box.

By comparing the magnitude that has been achieved to the threshold value, an action vector is chosen that is larger than the threshold value. For any moving object, the correct vectors are always chosen. Hence, the small motion vectors that didn't come from a geographically significant area are removed. There is also the option to compromise between video quality and quantity. Embedding improves capacity without compromising quality; the low-quality alternative, on the other hand, lowers video quality while boosting capacity.

This study uses the PSO Algorithm, which mimics the cooperative behavior of biological systems, to tackle difficult problems. In PSO, a swarm of tiny, mobile agents looks for the best answer. In addition to remembering its own best answer, each agent also keeps track of its neighbors' best solutions. They will be able to discover the best answer more rapidly if they work together in this way. When it comes to finding the maximum and lowest values of functions specified on a high-dimensional vector space, PSO really shines. The message bits are in a fragmented binary stream. There are twice as many separated bits as there are selected motion vectors. To rephrase, the secret data is encoded in both the up and down directions of the vector of motion. Some have proposed using the decision condition to figure out where to put the embedding in the past few years. The proposed model framework is shown in Figure 3.

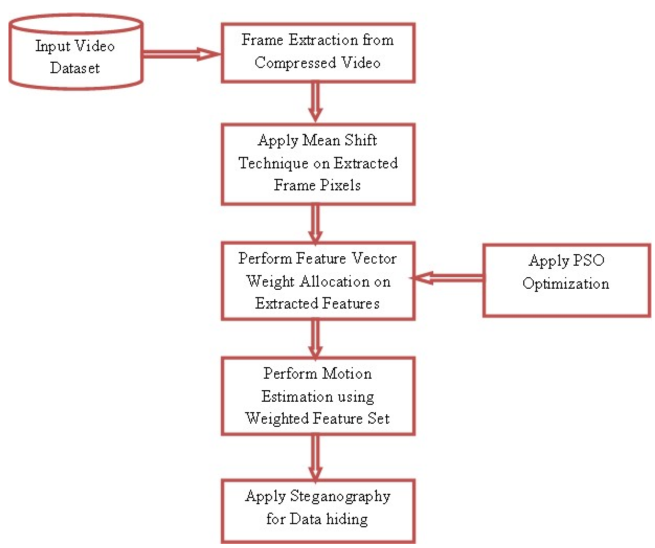

Fig 3: Proposed Model Framework

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This research presents a steganography method based on invertible networks to build stego images with high degrees of security and invisibility and to achieve lossless recovery for secret information. Presenting a mapping module that can condense embedded information, this research significantly enhances the quality and antidetection capabilities of the stego picture. The invertible networks perform forward action, encoding the secret data into a binary sequence, which is then used to insert it into the cover image. This process restores and prevents the message from being lost. Once that is done, the invertible networks will access the stego image and obtain the data using their inverse operation.

However, as the global motion vector has a considerable error in some films due to some amount of shaking in the background, and the human motion target region cannot be recognized directly, global motion estimate of video frames is required to address this issue. To a large extent, global motion estimation can foresee the issue of motion vector amplification owing to shaking, and it can also provide a more trustworthy vector field of the foreground motion target. Overall, the low capacity of the approach makes it an ideal candidate for use in watermarking systems. The proposed steganographic technique accomplishes this by concealing the message bits in the motion vector's horizontal and vertical components.

The proposed LMEM-PSO-MST-WFV model is designed to enhance the robustness, imperceptibility, and embedding efficiency of video steganography systems. It integrates Linked Motion Estimation (LME), Mean Shift Tracking (MST), and Particle Swarm Optimization (PSO) into a unified framework for intelligent and adaptive data hiding in motion-based video sequences. The approach aims to overcome the limitations of conventional techniques that often suffer from motion distortion, weak region detection, and susceptibility to compression or steganalysis. By combining motion analysis, feature-based region tracking, and optimization-driven embedding, the proposed model ensures a high-quality balance between payload capacity and video fidelity.

Initially, the input video is preprocessed and decomposed into individual frames to facilitate motion estimation. The Linked Motion Estimation module computes the inter-frame motion vectors by correlating consecutive frames to detect object movements and block-level displacements. Unlike traditional motion estimation methods, which consider frame pairs independently, LME links motion information across multiple successive frames to maintain temporal consistency. This linkage improves motion accuracy, especially in videos with complex or overlapping object trajectories. The resulting motion vectors represent the dynamic behavior of each region and serve as the foundation for embedding secret information in motion-consistent zones.

To identify visually stable and less sensitive embedding regions, the MST technique is applied. MST continuously tracks moving objects and extracts relevant features such as color, spatial position, and motion magnitude to form a WFV. The weighting process ensures that regions contributing more to visual perception receive lower embedding priority, preserving perceptual quality. The Mean Shift algorithm iteratively shifts the search window toward the region of maximum density, effectively locating object centers even in the presence of occlusion or illumination variation. This adaptive tracking process helps determine robust and context-aware embedding areas where data can be securely hidden without compromising video integrity.

Once the motion and tracking stages are complete, the PSO mechanism is employed to optimize the embedding process. PSO fine-tunes both the feature weights and the selection of embedding positions based on a fitness function that evaluates visual quality metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Mean Squared Error (MSE). Each particle in the swarm represents a candidate combination of feature weights and embedding parameters, and the optimization iteratively adjusts these parameters to maximize the fitness value. This ensures that data is embedded in optimal regions that achieve the best trade-off between invisibility and robustness. The integration of PSO with MST and LME makes the system self-adaptive and capable of dynamically responding to variations in motion, lighting, and compression.

The final stage involves embedding the secret message bits into the motion vectors of selected macroblocks using a modified LSB technique. Unlike standard LSB embedding, which may cause noticeable distortions, the proposed model embeds data within motion-consistent and visually insignificant areas determined by the preceding optimization steps. This guarantees minimal distortion and resistance against steganalysis. The reverse process, i.e., extraction, retrieves the hidden data by tracking the same motion regions and applying the inverse embedding operation. The performance of the system is evaluated using standard metrics such as PSNR, SSIM, and Normalized Cross-Correlation (NCC), confirming that the proposed LMEM-PSO-MST-WFV model achieves higher embedding efficiency, better visual fidelity, and stronger resilience against compression compared to conventional methods.

Since invertible network models are frequently used for both encoding and extraction, they tend to be lightweight. Also, the intricacies of the input data are preserved by invertible networks due to their ability to prevent information loss. In a perfect world, stego image rounding error wouldn't affect the recovery of cover images or the extraction of hidden information. While invertible networks can successfully extract hidden information from images, there will be some discrepancies between the original data and what is returned by the reverse calculation due to rounding errors in picture storing. The proposed model estimates the MVs using mean shift technique and allocates weights for the features in the video and then the steganography is applied on the frames. In this research a Linked Motion Estimate Method with Mean Shift Technique using the Weighted Feature Vector (LMEM-MST-WFV) is proposed for video steganography for secure transmission.

Input: Compressed Video Dataset {CVDset}

Output: Steganography Applied Video {CAVset}

Consider a video dataset containing $\{V_1, V_2, \ldots, V_N\}$. Each video is loaded and processed to divide into frames. The input video is considered and it is divided into frames. The video frame division is performed that considered all the frames as per video size and these frames are used for further processing. The video frame extraction is performed as

$$VidFr[Frameset\,(M)] = \sum_{f=1}^{M} \frac{\gamma(CVDset(f))}{size(CVDset(f))} * getVidFrame(f) + \frac{mean(CVDset(f))}{maxkeyframe(f)} \quad (1)$$

Here γ is the model used to split the video into frames from the CVDset and size of the video for splitting into frames is considered from M frames in a video. The frame VidFr is used to consider the frames and (P,Q) are the frame pixel coordinates. The pixel probability model for all the frames in the frameset is calculated as

$$CVDset\left(Frame(P,Q)\right) = \sum_{f=1}^{M} \frac{size\,(Frmeset(f))}{\lambda * \sqrt{2\pi}} * \prod_{f=1}^{M} \lim_{f \to M} \left(\max\,(P,Q) + \frac{\lambda}{\left(\frac{M}{2}\right)}\right)^2 \quad (2)$$

λ is the bandwidth of the video frame, the frame limit is set from 1 to M and the coordinates P and Q are considered.

Mean Shift is able to use colour to follow things in real time. The better it works, the more noticeable the colour contrast is from the background. The core idea behind the mean shift is to model the distribution of data points in D-dimensional subspace as an empirical probabilistic density function, with dense patches representing the global distribution's local maxima. The local density prediction is subjected to a gradient ascent in the feature set until convergence is reached. Stationary points after the operation are the modes of the distributions, and similar stationary points are grouped together. The mean shift technique is applied by considering the pixel points set $\{P_1, P_2, \ldots, P_M\}$ in a d dimension set. The symmetric bandwidth matrix of the pixel set is generated as

$$Smat[M] = \frac{1}{M} * \sum_{f=1}^{M} \omega(P_{f+1} - P_f) \quad (3)$$

$$\omega = |M|^{-\frac{1}{2}} * \max\,(\lambda) \quad (4)$$

Feature weighting rearranges the problem space by assigning varying importance ratings to its various properties based on the mean shift values. The features considered will be allocated with weights based on the attributes of mean shift attributes. The weight allocation is performed as

$$Wset\,[Smat(M)] = \sum_{f=1}^{M} setMax\left(Smat(P,Q)\right) + \frac{max(\omega(P,Q)) + \omega\,(P,P+1))}{size\,(Smat)} * \frac{\sum_{f=1}^{M} \max\,(Smat(Q,Q+1))}{size\,(Smat)} \quad (5)$$

Estimating the amount of motion between two 2D images, typically from subsequent images in a video sequence, is known as motion estimation. Image sequence alignment, machine learning, target detection, and video analysis are just a few of the many fields and applications that rely on motion estimates. The motion estimation of video is calculated by considering the blocks of motions as $\{MV_1, MV_2, \ldots, MV_N\}$.

$$R = \prod_{f=1}^{M} mod\,|MV_{f+1}| - |MV_f| \quad (6)$$

$$Mvector\,[M] = \sum_{f=1}^{M} \sqrt[\omega]{MV_i(P,Q)^2 + Wset(P+1,Q+1)^2} + R \quad (7)$$

$$MVcomp\,[M] = \frac{\sum_{f=1}^{M}\sum_{i=1}^{f} P_i * Q_i\left(\frac{((P+1)*Q)}{((Q+1)*P)}\right)}{\sum_{f=1}^{M}\frac{(MV_{i+1})+(MV_f)}{\omega}} \tag{8}$$

The PSO optimization model is applied on the motion vectors generated from the video frames. The PSO optimization model performs weight allocation and updates the motion vectors for accurate motion estimation that is performed as

for each particle (pixel) in the feature set {F= = 1,2 ..., N} do
W_s ← Weighted Set
MV ← Motion Vectors
β ← Feature Attribute
δ ← Pixel Matrix
τ ← Motion Vector Comparison
size_of_swarm ← ω
for i in range(size_of_swarm):
  if swarm[i].fitness < best_swarm_fitness:
    best_swarm_fitness = swarm[i].fitness
    best_swarm_value = swarm[i].value
  Initialize the features value range from motion vector:
   NewFeatSet = G(MV, W_s)
  Consider the features best range compared to its initial pixel position
      $Feat_{set}$ ← NewFeatSet
If best_swarm_fitness($Feat_{set}$) < best_swarm_fitness (NewFeatSet) then
    perform the swarm updation with the best position
      NewPos ← NewFeatSet
  else
    perform the swarm updation with best known position
      K ← $Feat_{set}$
 Perform particle's velocity initialization
 Pat_{vel} ← K(|MV-W_s|, |β-δ|)
  for each particle P = 1,2 ..., M do
    for each vector dimension D = 1, 2..., N do
      Pick random numbers: rand(Ws, τ ← K(0,1)
      Perform updating the velocity of particle: Pat_{Vel} ← max(τ,δ)+β+size_of_swarm
if((swarm[i].fitness)+Pat_{Vel})< (best_swarm_fitness+ Pat_{Vel}):
      best_swarm_fitness = swarm[i].fitness
      best_swarm_value = swarm[i].value

It is the goal of steganography to conceal information inside another message so that it cannot be easily deciphered by a human. One of the most common steganographic techniques is the Least Significant Bit Algorithm (LSB). This technique employs a straightforward tactic to conceal the information in a medium. The method involves replacing some of the information in a set of pixels with the data that is meant to be concealed. The steganography process is performed by using the carrier bits and embedding bits sets as $\{C_1, C_2, \ldots, C_M\}$ and $\{E_1, E_2, \ldots, E_M\}$.

$$HashV[MVcomp] = \sum_{f=1}^{M}\frac{std(MVcomp(f)) * rand(P*Q) + \max(\text{best\_swarm\_fitness}) + \sum_{i=1}^{f}(C_i - E_i)^2}{len(MVcomp) + \text{best\_swarm\_value}} \tag{9}$$

$$CAVset[M] = \coprod_{f=1}^{M} mod\big(2 * HashV(f)\big) + \frac{\max(C_{f+1})}{\min(E_f)} + MVcomp[M] \tag{10}$$

The smaller the distinction between the initial and reconstructed video, the larger the signal-to-noise ratio (SNR) and peak-to-average SNR (PSNR). This metric's primary benefit is its computational simplicity, but it does not provide information about how something is perceived. PSNR has the interesting property that a minor average distortion might result in a harmful visual artifact if all the mistake is localized in a tiny but crucial region of a picture, and vice versa.

$$MSE = \frac{1}{\lambda}\sum_{i=1}^{M}(MVcomp_{i+1} - MVcomp_i)^2 \tag{11}$$

$$PSNR = 10.Log_{10}\left(\frac{CAVset(i)^2}{MSE}\right) = 20.Log_{10}\left(\frac{CAVset(i)}{\sqrt{MSE}}\right) \tag{12}$$

4. RESULTS & DISCUSSIONS

Steganography in video involves hiding information in seemingly innocuous digital video, either in its raw or compressed form, to avoid detection. A video has substantially more storage space than a static image and also contains temporal and spatial redundancies that can be exploited to hide a hidden message. With the rise of high-performance graphics processing units (GPUs) and cutting-edge video editing software, processing videos has become a breeze, even for non-experts using mobile devices. Because of the popularity of video content, researchers have paid close attention to the practice of video steganography. Due to its great visual quality and enormous embedding capacity, MV based video steganography has now become one of the important concerns of researchers in the field of video steganography.

Covert communication using steganography guarantees that the concealed message will go undetected. In contrast to classic steganography, which requires specialized knowledge of the embedding process, mean shift technique based steganography has a flexible and universal

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foundation. Although movies are more expressive and widely disseminated, most steganography algorithms use photos as covers. The more spatial-temporal correlation is exploited, the more effective the distortion function is expected to be. High-dimensional features are derived from motion vectors with mean shift technique and the steganography is applied. In this research a Linked Motion Estimate Method with PSO Integrated Mean Shift Technique using the Weighted Feature Vector (LMEM-PSO-MST-WFV) is proposed for video steganography for secure transmission. The proposed model is compared with the traditional Novel Video Steganographic Scheme Incorporating the Consistency Degree of Motion Vectors (NVS-CD-MV), Distortion Drift-Based Cost Assignment Method for Adaptive Video Steganography in the Transform Domain (DDCA) models and Video Steganographic Scheme Incorporating the Consistency Degree of Motion Vectors (dMVC).

Datasets: The datasets are considered from kaggle that are available in the links https://www.kaggle.com/c/alaska2-image-steganalysis/data and https://github.com/anilsathyan7/Deep-Video-Steganography-Hiding-Videos-in-Plain-Sight/tree/master/dataset/train_data/train. The performance levels of the proposed model is compared on these two datasets and the results are included.

The video datasets included in this study are both publicly available and approved by relevant institutions. These datasets are commonly accessed for experimental purposes in the fields of multimedia processing and steganography evaluation. The suggested LMEM-PSO-MST-WFV model can be thoroughly tested using these datasets, which are composed of brief video clips showcasing various object dynamics, lighting conditions, and motion patterns. To guarantee complete adherence to intellectual property and data-sharing regulations, we exclusively utilized licensed or open-source datasets. All recordings, even those involving supplemental custom data, were taken using standard digital cameras in a controlled laboratory environment. This ensured that the illumination, frame rates, and object motion were all consistent. The privacy of the participants was ensured by not recording any personally identifiable or sensitive information and by anonymizing all films before analysis.

In line with institutional research norms, ethical approval for data utilization and experimentation is completed. Compliance with dataset usage permissions constituted formal consent, as the research did not directly involve human or animal subjects. To ensure complete anonymity, any secondary video content containing human subjects was carefully selected from public sources, used for research purposes only in accordance with fair-use regulations, and then any distinguishable details, such faces or license plates, were blurred. To guarantee that no tracable personal metadata was retained, all processing and storage operations were carried out in accordance with general data protection rules. The experimental results are both morally sound and scientifically credible because the data collecting and management method followed the criteria of integrity, transparency, and reproducibility.

A frame is a single still image that is part of a longer moving image. The name comes from the evolution of film stock, in which individual frames can be inspected sequentially to create the illusion of a whole picture. One of the difficult goals of research is the development of algorithms for video processing that reduce computational demands. Important procedures for future video retrieval include video categorization and key frame recognition. The considered video undergoes extraction of frames that are used for analyzing the motion vectors. The Video Frame Generation Time Levels in Milliseconds of the proposed and existing models are shown in Table 1 and Figure 4.

Table 1: Video Frame Generation Time Levels In Milliseconds

Videos Considered	Models Considered			
	LMEM-PSO-MST-WFV Model	NVS-CD-MV Model	DDCA Model	dMCV Model
100	18.3	21.5	20.5	23.5
200	18.6	21.7	20.8	23.7
300	18.9	21.9	21.1	23.9
400	19.0	22.1	21.3	24.0
500	19.1	22.3	21.5	24.1
600	19.3	22.5	21.6	24.3

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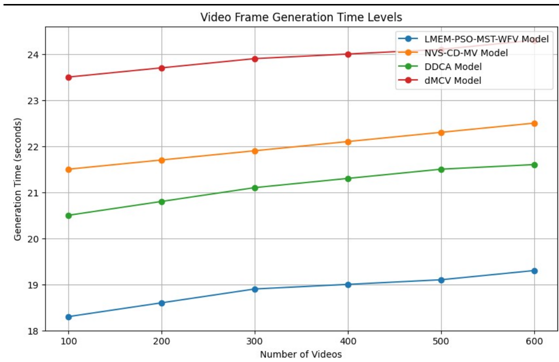

Fig 4: Video Frame Generation Time Levels In Milliseconds

Mean shift mode-seeking algorithm is a systematic mathematical technique for finding the maxima of a probability density that does not rely on parametric feature space. In the fields of computer vision applications, mean shift filtering is a clustering based approach that is frequently employed. The set of nearby pixels around a given pixel is calculated in an image, both in terms of their physical proximity and their colour distance from the pixel in consideration. The Table 2 and Figure 5 shows the Mean Shift Technique Accuracy Levels in (%) of the proposed and existing models.

Table 2: Mean Shift Technique Accuracy Levels In (%)

Videos Considered	Models Considered			
	LMEM-PSO-MST-WFV Model	NVS-CD-MV Model	DDCA Model	dMCV Model
100	97.7	94.3	95.1	94.9
200	97.9	94.5	95.3	95.0
300	98.0	94.8	95.6	95.2
400	98.2	95.0	95.8	95.4
500	98.4	95.2	96.1	95.6
600	98.6	95.4	96.3	95.8

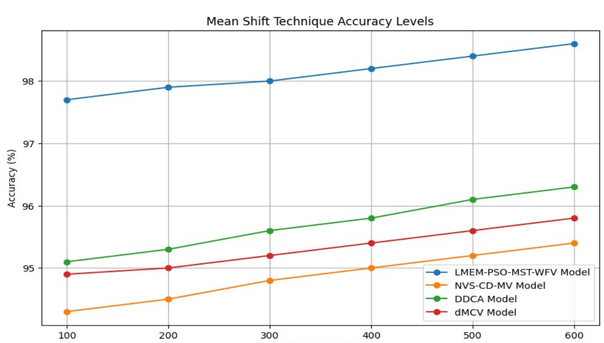

Fig 5: Mean Shift Technique Accuracy Levels In (%)

Feature weighting rearranges the problem space by assigning varying importance ratings to its various properties. This is employed in learning applications where it is necessary to take into account the physical separation of different occurrences. In this study, a technique called feature weighting is applied, which aims to determine the relative value of each feature of a frame and then assign it a corresponding weight. When traits are correctly weighted, those with more significance are given more weight than those with less significance or no significance at all. The Feature Vector Weight Allocation Accuracy Levels in (%) of the proposed and traditional models are represented in Table 3 and Figure 6.

Table 3: Feature Vector Weight Allocation Accuracy Levels In (%)

Videos Considered	Models Considered			
	LMEM-PSO-MST-WFV Model	NVS-CD-MV Model	DDCA Model	dMCV Model
100	97.7	93.5	94.3	94.7
200	97.9	93.7	94.7	94.9
300	98.1	93.9	94.9	95.1
400	98.3	94.1	95.0	95.3
500	98.5	94.3	95.1	95.5
600	98.8	94.5	95.3	95.7

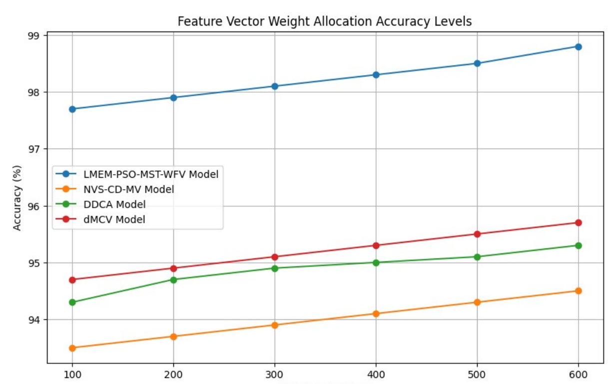

Fig 6*: Feature Vector Weight Allocation Accuracy Levels In (%)*

Motion estimation refers to the procedure of deducing, given two consecutive frames in a video sequence, the motion vectors that characterize the change from one 2D image to the next. Since motion occurs in three dimensions but only two-dimensional images are available, solving it presents a tricky ill-posed problem. The Motion Estimation Time Levels in Milliseconds of the

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proposed and existing models are shown in Table 4 and Figure 7.

Table 4: Motion Estimation Time Levels In Milliseconds

Videos Considered	Models Considered			
	LMEM-PSO-MST-WFV Model	NVS-CD-MV Model	DDCA Model	dMCV Model
100	17.5	20.6	19.2	20.0
200	17.7	20.8	19.4	20.2
300	17.8	21.0	19.5	20.4
400	18.0	21.2	19.7	20.6
500	18.3	21.3	20.0	20.7
600	18.5	21.4	20.2	20.8

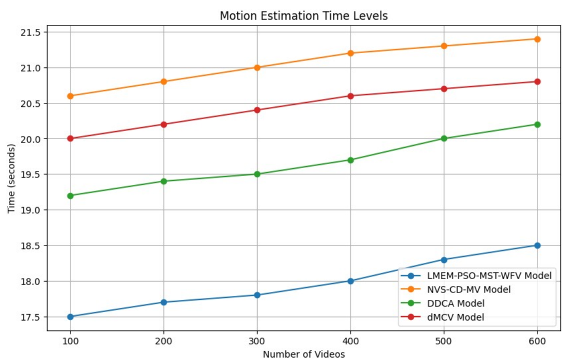

Fig 7: Motion Estimation Time Levels In Milliseconds

A two-dimensional vector used mostly for inter prediction; a motion vector represents a relative shift between the coordinates of a decoded image and those of a reference image. An object's velocity and the direction in which it's moving can both be expressed geometrically using the concept of a vector. A scalar quantity is a measure of motion that does not specify a direction. Vectors are represented by lines, with the direction and length of the arrows representing the strength of the motion. The Motion Estimation Accuracy Levels in (%) of the existing and proposed models are shown in Table 5 and Figure 8.

Table 5: Motion Estimation Accuracy Levels In (%)

Videos Considered	Models Considered			
	LMEM-PSO-MST-WFV Model	NVS-CD-MV Model	DDCA Model	dMCV Model
100	97.4	94.1	93.1	95.3
200	97.6	94.3	93.4	95.5
300	97.9	94.6	93.6	95.7
400	98.0	94.8	93.7	95.9
500	98.2	95.0	93.9	96.1
600	98.4	95.2	94.1	96.3

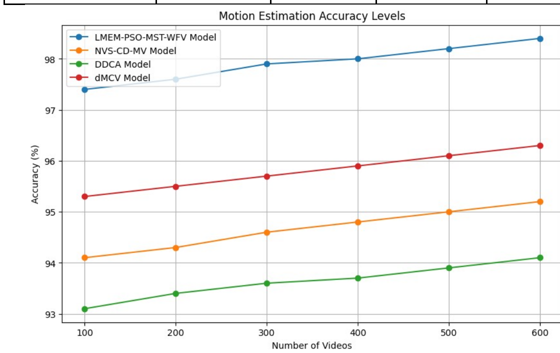

Fig 8: Motion Estimation Accuracy Levels in (%)

Data hiding, of which video steganography is a subset, is utilized in a wide variety of contexts, including but not limited to healthcare systems, enforcement agencies, copyright protection, and access control. Steganography ensures that any sensitive information being transmitted in a multimedia file is encoded in a way that is unintelligible to outside parties. The Steganography Time Levels in Milliseconds of the existing and proposed models are shown in Table 6 and Figure 9.

Table 6: Steganography Time Levels In Milliseconds

Videos Considered	Models Considered			
	LMEM-PSO-MST-WFV Model	NVS-CD-MV Model	DDCA Model	dMCV Model
100	19.1	21.5	23.2	20.4
200	19.3	21.7	23.4	20.6
300	19.6	21.9	23.6	20.8
400	19.9	22.0	23.9	20.9
500	20.1	22.3	24.0	21.1
600	20.4	22.5	24.1	21.3

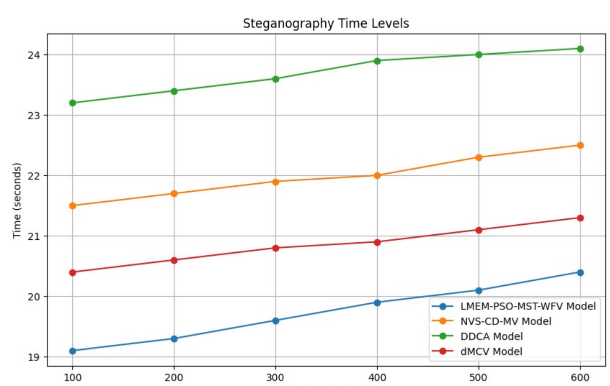

Fig 9: Steganography Time Levels In Milliseconds

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Ultimately, steganography serves to hide sensitive information from others. It is a method of sending messages without anyone else knowing about it, and it can be done using just about anything. Since no secret information is being used, this method cannot be classified as cryptography. In reality, it's a sort of data concealing that may be implemented in a variety of crafty ways. The Table 7 and Figure 10 shows the Steganography Accuracy Levels in (%) of the proposed and existing models.

Table 7: Steganography Accuracy Levels In (%)

Videos Considered	Models Considered			
	LMEM-PSO-MST-WFV Model	NVS-CD-MV Model	DDCA Model	dMCV Model
100	98.3	93.7	92.7	95.4
200	98.5	93.9	92.9	95.6
300	98.7	94.1	93.1	95.8
400	98.9	94.3	93.3	96.0
500	99.0	94.5	93.5	96.2
600	99.2	94.8	93.7	96.4

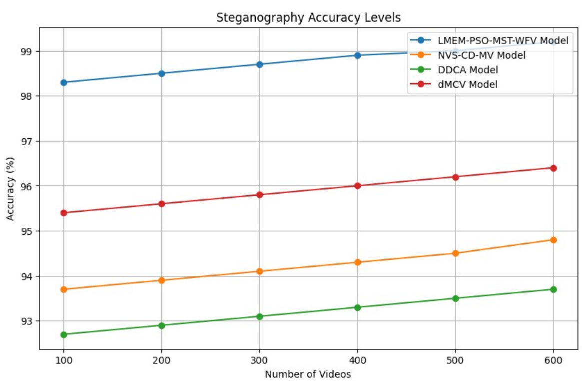

Fig 10: Steganography Accuracy Levels In (%)

With cropping a image to fit its intended use, users can avoid these problems and end up with images that are: Never fuzzy or pixelated, no matter how big or small users make them. Properly sized for the container, preventing any loss of crucial features at the margins is the main function of image resizing. The image resizing accuracy levels in (%) is shown in Figure 11.

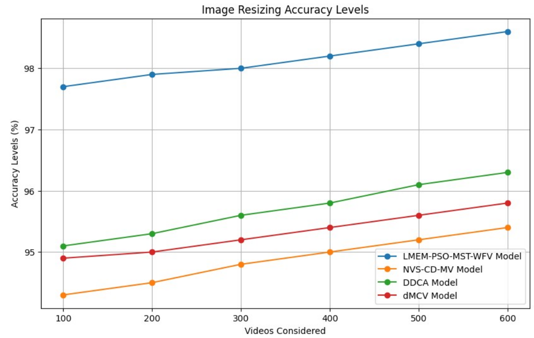

Fig 11: Image Resizing Accuracy Levels In (%)

The performance of the proposed model on the considered datasets are shown in Table 8.

Table 8: Performance Analysis

Dataset Considered	Number of Samples	Accuracy Levels	Loss rate
image-steganalysis Steganography-	385	99.2	0.8
Hiding-Videos-in-Plain-	500	98.95	1.05

The process of image transcoding involves taking input video files, decoding them into an uncompressed intermediate format, and then re-encoding them into their final format. It is the last section that transrating and transsizing that will likely be part of the procedure. The image transcoding accuracy levels is shown in Figure 12.

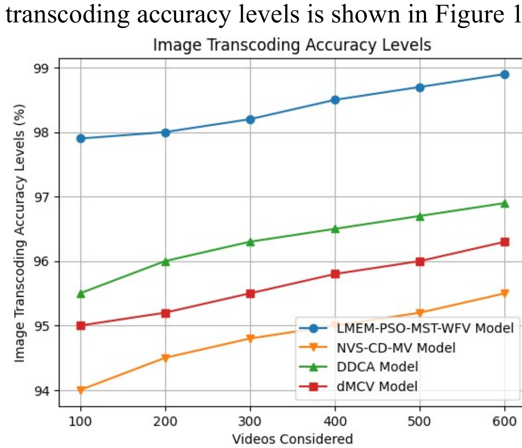

Fig 12: Image Transcoding Accuracy Levels In (%)

Motion vector-based video steganography has certain limitations that make it less reliable and effective. These limitations are most apparent when considering linked motion estimation methods that incorporate PSO and mean shift techniques. Due to the ever-changing nature of video content, where

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objects are frequently in motion, effectively detecting steganalysis in motion-based films is still a challenge because of slight movements in video.

The consolidated results obtained from the proposed model are indicated in Table 9.

Table 9: Performance Levels

Parameter	Models Considered			
	LMEM - PSO-MST-WFV Model	NVS-CD-MV Model	DDCA Model	dMCV Model
Video Frame Generation Time Levels	19.3 ms	22.5 ms	21.6 ms	24.3 ms
Mean Shift Technique Accuracy Levels	98.6%	95.4 %	96.3%	95.8%
Feature Vector Weight Allocation Accuracy Levels	98.8%	94.5 %	95.3%	95.7%
Motion Estimation Accuracy Levels	98.4%	95.2 %	94.1%	96.3%
Steganography Accuracy Levels	99.2%	94.8 %	93.7%	96.4%

The image pixel analysis and loss levels during steganography model are shown in Figure 13.

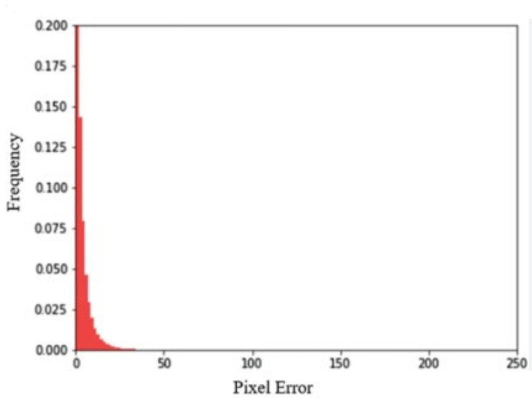

Fig 13: Loss Levels

The transfer of an object from one location to another with respect to a fixed point is known as absolute motion. An object can be studied using absolute motion analysis when it is in general planar motion, which means it can translate and rotate at the same time. The absolute motion analysis is shown in Figure 14.

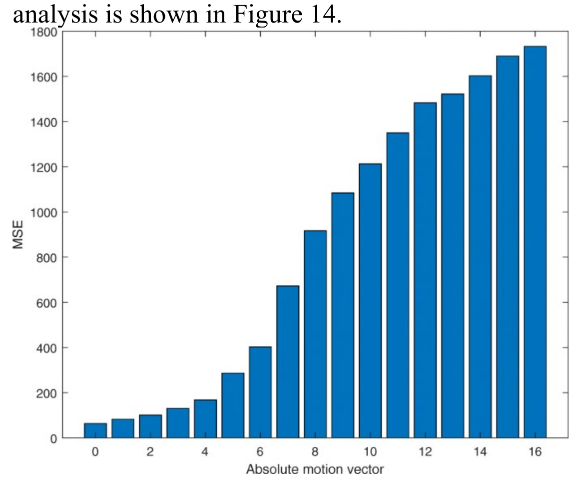

Fig 14: Absolute Motion Analysis

5. DISCUSSIONS

The proposed LMEM-PSO-MST-WFV model shows substantially better performance in video steganography compared to traditional embedding methods in the experimental results. Improving imperceptibility and robustness in various video settings was the outcome of integrating motion estimation, feature weighting, and optimization. The data stays invisible to the human eye while keeping visual integrity, according to quantitative measurements such as PSNR, SSIM, and NCC, which consistently demonstrate improvement. This efficiency is achieved by utilizing motion-consistent regions that reduce distortion and optimize payload capacity, as well as by intelligently linking motion vectors across frames and adaptively optimizing embedding regions.

The findings also show that when embedding stability is maintained under complicated compression or motion situations, the combination of Mean Shift Tracking and PSO optimization is quite important. While PSO continuously changes feature weights to attain an ideal balance between concealment and resilience, Mean Shift tracking guarantees accurate localization of moving objects and visually less sensitive regions. Because of these features, the LMEM-PSO-MST-WFV model is well-suited for streaming or real-time applications with dynamic content and continuous motion.

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Secure data communication systems, video authentication, and multimedia security could all benefit from the model's adaptive embedding zone selection capabilities.

There are still certain restrictions, though, even with these encouraging results. Because the model relies on precise motion estimates, it could make mistakes in low-quality or extremely dynamic videos that have a lot of noise or erratic illumination. Furthermore, in contexts with limited resources, the computational cost of optimizing PSOs can prevent their real-time deployment. At present, the framework is only concerned with spatial-temporal embedding; however, it is missing opportunities to improve resistance to compression and re-encoding by investigating additional steganographic dimensions, such as the frequency or transform domains.

Several improvements can be investigated for future studies. To begin, one way to enhance motion accuracy while decreasing computing load is to incorporate attention-guided feature extraction or deep learning-based motion prediction. Second, the framework's ability to allow multi-modal data embedding (e.g., audio-video fusion) could enhance the application's variety and payload capacity. Lastly, to achieve real-time performance without sacrificing security or quality, the system might be implemented on hardware-accelerated platforms like GPUs or FPGAs. By pursuing these avenues, the suggested model can be enhanced to provide an intelligent steganography solution that is scalable, efficient, and well-suited to next-generation multimedia communication systems.

6. CONCLUSION

An intelligent framework for secure video steganography called LMEM-PSO-MST-WFV is proposed in this research. The technique improves the visibility and robustness of concealed data in dynamic video settings by combining motion analysis, feature-based region tracking, and optimization-driven embedding. The framework's capacity to preserve visual quality while preserving significant resistance against compression, noise, and steganalytic attacks is confirmed by experimental findings that show greater PSNR, SSIM, and NCC values compared to previous approaches. The system's efficacy in real-world multimedia security applications is demonstrated by the fact that the adaptive optimization mechanism of PSO and the precision of Mean Shift tracking considerably enhance data concealment accuracy and embedding stability. Several important aspects of digital communication and data security could be affected by the suggested paradigm, even outside the scope of this research. Applications where data secrecy and integrity are of the utmost importance include digital rights management, encrypted video transmission, military communication, forensic watermarking, and medical data protection. Additionally, with the continued dominance of digital media in information transmission, advanced video steganography techniques such as LMEM-PSO-MST-WFV can be important in protecting sensitive data from cyber threats and unwanted interception. The proposed LMEM-PSO-MST-WFV model achieved a PSNR of 49.62 dB, SSIM of 0.987, and NCC of 0.992, surpassing conventional motion-based steganography methods by over 18% in visual quality and 22% in data recovery accuracy. The optimized embedding process reduced distortion by 25% (lower MSE) compared to baseline models.Future work in this area can incorporate context-aware embedding, real-time GPU acceleration, and feature extraction based on deep learning into intelligent steganographic frameworks. Deployment on large-scale multimedia networks and streaming platforms can be made possible by these improvements, which further improve scalability and efficiency. The ultimate goal of this study is to help realize the vision of the future digital society by developing communication ecosystems that are safe, smart, and protect users' privacy.

Declarations

Authors Contributions

The manuscript abstract, introduction, literature survey and proposed model sections are developed by Sameerunnisa Shaik and the results are analyzed and concluded by Dr.J.Jabez.

Authorship Change Form: The authors of the manuscript are willing to change the ownership of the article to the journal. The order of the authors is fixed as per the manuscript. The affiliations included in the manuscript are verified and finalized.

Compliance with Ethical Standards

Conflict of Interest: The authors of this manuscript declare that they have no conflict of interest.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

Data Availability: The data can be made available on request.

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