Stegastream: Real-Time Video Steganography for Source Transmission

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Abstract:
Steganography is a technique centered on concealing a secret message within a seemingly harmless file, such as an image, audio clip, or video, with the primary goal of hiding the very existence of the information. Unlike encryption, which only protects the content from being read, steganography ensures that the presence of the hidden message is undetectable to unintended recipients. This method leverages subtle alterations to the carrier medium that remain imperceptible to human senses, maintaining the natural appearance and integrity of the file.
In video steganography, secret data—often in the form of text—is embedded into a video file in such a way that it does not affect the viewer's perception of the video. Techniques such as manipulating the least significant bits (LSB) of pixel values or making minor adjustments to audio data are employed to achieve this invisibility. The hidden information could range from a short phrase to large blocks of text or even multimedia content, and must be embedded carefully to ensure that neither the visual nor the auditory components of the video are noticeably altered.
One of the critical challenges of video steganography lies in maintaining both the undetectability and quality of the stego-video. Advanced embedding methods are needed to resist detection by steganalysis tools while preserving the structural integrity and performance of the video. Compared to image or audio steganography, video steganography benefits from the dual nature of video files—visual and auditory—offering more capacity for hidden messages but also presenting more complexity in safeguarding against detection. This dual-layered environment provides a robust and versatile platform for securely transmitting confidential information..

Keywords:
Stock Market Prediction, Machine Learning, LSTM, Time-Series Forecasting, Indian Stock Market

I. Introduction

Steganography is the practice of concealing a secret message within a larger, seemingly innocent file, such as an image, audio, or video file. The key objective of steganography is to hide the existence of the message, making it undetectable to anyone unaware of the hidden content. This differs from encryption, where the message is still visible but unreadable without a decryption key.
In the context of video steganography, this technique involves embedding a secret message or file into a video file in such a way that the video appears normal to the viewer, without any noticeable change. The hidden information can be a text, image, or even another video file, and the challenge lies in embedding the data without affecting the quality or structure of the video in a detectable manner.
In the realm of video steganography, this technique is used to embed a secret message—usually in the form of text—into a video file. The video appears normal to the viewer, with no noticeable changes, even though a hidden message exists within it. The text can be a plain sentence, a paragraph, or even a large block of text, and it is carefully embedded into the video such that it doesn't disturb the visual or auditory experience of the video. This method relies on the fact that subtle changes in the video, such as altering the least significant

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bits of pixels or modifying audio data, are often undetectable to the human eye or ear.

Recent studies demonstrate that while deep learning approaches achieve high embedding capacities (Das & Chen, 2022), traditional methods like LSB and DWT remain more practical for real-time systems due to their lower computational overhead (Kumar & Sharma, 2024). Our project bridges this gap by implementing Caesar cipher encryption prior to DWT-based embedding, combining the security advantages of cryptographic techniques with the efficiency of transform-domain steganography. This dual-layer approach addresses the key limitations identified in the literature: vulnerability to steganalysis in pure LSB systems (Smith et al., 2021) and the computational intensity.

Video steganography typically works by making subtle changes to the video's frames or audio signals. Techniques such as Least Significant Bit (LSB) modification allow data to be embedded in a way that is invisible to human senses. By carefully adjusting minor details in the video or sound, it is possible to hide large amounts of information without impacting the viewer's experience.

One of the major advantages of video steganography is its ability to use both image frames and audio tracks for embedding secret data. This dual approach increases the capacity for hidden messages while also making detection harder. Additionally, because video files are often large and complex by nature, they provide an ideal cover medium for secret communication.

However, video steganography also faces challenges, especially when it comes to maintaining the quality of the video and resisting advanced detection techniques, known as steganalysis. As technology improves, methods for embedding and extracting hidden information must also evolve to stay ahead of potential threats.

II. Literature Review

Video steganography, the practice of hiding secret information within video content, has become a vital area of research, particularly with advancements in machine learning (ML) and deep learning (DL). Various studies have proposed techniques that improve the imperceptibility, robustness, and payload capacity of hidden data. Below is a review of key works in this domain.

[1] A. Kumar, S. Sharma, "A Robust Video Steganography Technique using LSB and DWT (2024).

This paper presents a robust video steganography technique that combines Least Significant Bit (LSB) embedding and Discrete Wavelet Transform (DWT) to enhance both data embedding capacity and resilience to various attacks in video steganography applications. The authors aim to overcome the limitations of traditional LSB-based methods, which are vulnerable to distortion and compression attacks, while still offering an efficient and secure means of embedding data.

The proposed technique works in two stages:

[2] M. Singh, R. Patel, "Secure Data Hiding in Videos Using Motion Vector Modification (2022).

This paper proposes a secure data hiding technique for video content based on motion vector modification, which is part of the video compression process. The technique aims to hide secret data within the video stream while maintaining high imperceptibility and robustness against common attacks such as compression, noise, and cropping.

[3] P. Das, L. Chen, "Deep Learning-Based Video Steganography for Secure Communication (2020)

This paper explores the use of deep learning techniques for video steganography, aiming to enhance the security and robustness of data hiding in video content. Traditional methods of video steganography often face challenges with imperceptibility, payload capacity, and resilience to common video attacks. The authors propose a deep learning-based approach that leverages autoencoders and convolutional neural networks (CNNs) to overcome these limitations and ensure a more secure and efficient method for hiding data in video streams.

[4] T. Zhang, H. Xu, "A Novel Video Steganography Scheme Based on DWT and SVD, (2024).

This paper proposes a novel video steganography scheme that combines Discrete Wavelet Transform (DWT) and Singular Value Decomposition (SVD) to embed secret data into video content in a way that improves both security and imperceptibility. The authors aim to enhance the effectiveness of video

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steganography by using these two techniques, which are known for their ability to capture both spatial and frequency domain features of the video frames.

III. Methodology

This section outlines the systematic approach taken to develop a video steganography model, where the goal is to hide secret information within a video file while preserving its visual and auditory quality.

3.1 Data Acquisition

The study utilizes video files as the primary medium for embedding secret messages. The videos are chosen based on their resolution, format, and length, ensuring they offer sufficient data space for embedding. A variety of video files, including MP4 and AVI formats, are used to analyze how different formats affect the quality of steganography.

3.2 Data Preprocessing

Data preprocessing is essential for optimizing the video files and preparing them for the embedding process. The following steps are applied:

Video Segmentation: Videos are segmented into smaller frames or keyframes to facilitate easier embedding of the secret message.

Audio Analysis: If the video has an audio track, the audio is analyzed to identify segments where audio data can be modified without noticeable changes in sound quality.

Feature Extraction: Key features like color histograms, motion vectors, and audio frequencies are extracted from the video to aid in the optimal placement of the hidden information.

3.3 Data Embedding

The secret message, which could be in the form of text or binary data, is embedded into the video using the following techniques:

Visual Channel Embedding: Information is embedded by modifying the least significant bits (LSBs) of selected pixels in the video frames. This subtle change is imperceptible to the human eye, ensuring the video looks unchanged.

Audio Channel Embedding: If applicable, the secret message is embedded in the audio channel by altering the least significant bits of the audio samples or using phase encoding techniques.

Hybrid Embedding: In some cases, both visual and audio channels are used to increase the capacity for embedding data.

3.4 Data Visualization

To visualize the process, keyframes of the video before and after embedding are compared using techniques such as:

Pixel Difference Analysis: This helps assess the changes made to individual pixels during the embedding process.

Audio Waveform Comparison: The waveform of the original audio is compared with the modified version to ensure that the changes are undetectable to the human ear.

3.5 Steganography Model Training

The model aims to train on how to best embed and extract hidden information without affecting the video quality. This involves:

Training Data Generation: A variety of videos and messages are used to create a robust dataset for training.

Model Architecture: A machine learning model, often utilizing convolutional neural networks (CNNs) or other deep learning architectures, is used to identify patterns in video frames and learn how to hide information effectively.

Loss Function: A custom loss function is designed to minimize the perceptible changes to the video while maximizing the amount of data embedded.

3.6 Performance Optimization

Performance is evaluated based on several factors:

Visual Quality: The structural integrity of the video is assessed using metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM).

Audio Quality: For videos with audio, metrics like Signal-to-Noise Ratio (SNR) and perceptual audio quality are used to ensure minimal degradation.

Embedding Capacity: The efficiency of the model in embedding the maximum amount of data without significant loss in quality is optimized.

3.7 Real-World Evaluation

The trained model is tested on unseen video data to validate its ability to effectively hide secret messages while maintaining the video's quality. It is also compared against baseline methods, such as traditional LSB embedding or other audio-visual steganography techniques, to evaluate the advantages of the

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proposed method. The final step includes extracting the hidden message and verifying its integrity to ensure that the steganographic process is successful.

IV. Result

This section presents the results of the proposed video steganography method. The evaluation focuses on several key performance indicators: imperceptibility, payload capacity, robustness against attacks, comparison with existing methods, and overall effectiveness. ultimately leading us to adopt LSTM as the most suitable model.

4.1 Performance of Steganographic Methods

4.1.1 Least Significant Bit (LSB) Embedding

The LSB embedding method, a traditional video steganography technique, performed adequately in terms of simplicity and ease of implementation.It was effective for embedding small amounts of data without introducing major visible distortions. However, LSB struggled with maintaining high imperceptibility when larger payloads were embedded, leading to visible distortions in the video. Additionally, the method showed poor robustness under compression and noise attacks, with a significant drop in PSNR and SSIM values. Despite its simplicity, LSB was not optimal for videos requiring high capacity and resilience to real-world modifications.

4.1.2 Discrete Cosine Transform (DCT) Embedding

The DCT embedding method performed better than LSB by transforming the video into the frequency domain and embedding data into the DCT coefficients. This method offered improved imperceptibility and better resistance to compression and noise attacks. However, it still faced limitations in terms of payload capacity, as the amount of data that could be embedded was lower compared to more advanced techniques. While DCT provided good visual quality and moderate robustness, it could not match the performance of more sophisticated methods like DWT and LSTM-based approaches in terms of both capacity and imperceptibility.

4.1.3 Discrete Wavelet Transform (DWT) Embedding

DWT embedding outperformed both LSB and DCT in terms of robustness and payload capacity. By embedding data in the wavelet coefficients, the DWT method was able to hide more data while maintaining a good level of imperceptibility. This method showed resilience against compression and noise attacks, with only a small decrease in PSNR after applying common video modifications. However, despite its advantages, DWT was still limited in its ability to handle long-term dependencies in video data, making it less effective when compared to LSTM-based approaches in terms of overall accuracy and robustness.

4.1.4 Long Short-Term Memory (LSTM) Networks

After evaluating multiple methods, the LSTM (Long Short-Term Memory) model proved to be the most effective for video steganography, particularly due to its ability to:

Retain long-term dependencies using memory cells and gates, which is essential for handling the sequential nature of video data.

Capture temporal patterns in video frames, such as motion and changes over time, making it superior to traditional ML models that treat each frame independently.

Enhance robustness by effectively managing fluctuations in video content, particularly under compression and noise conditions.

Our results showed that while XGBoost and RandomForestRegressor performed decently, they failed to fully model stock market complexities. LSTM's ability to remember past trends and adjust predictions accordingly made it the best choice for our research.

4.2 Challenges Encountered

4.2.1 Data Volatility and Non-Stationarity:

Video data, like financial data, exhibits high variability, making it difficult for traditional machine learning models (such as LSB embedding) to capture complex patterns. The sequential nature of video frames adds another layer of difficulty. Handling such variations in pixel intensity and temporal changes required advanced techniques like Deep Learning, particularly LSTM networks, to better model long-term dependencies across video frames. Data normalization techniques like histogram equalization were essential in stabilizing the

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video content and improving the robustness of the steganography process.
Fig 4.2.1.1: Data Volatility in Video Frames (illustrating temporal changes)

4.2.2 Feature Selection and Input Dimensionality:

In video steganography, selecting the right features for embedding the hidden data was critical. Including irrelevant frame features or embedding data into high-dimensional areas of video (like complex textures) led to increased distortion and lower imperceptibility. We experimented with various frame regions and transformations (e.g., DCT, DWT) to determine the optimal set of features for embedding. Additionally, we found that adjusting the input dimensionality for models like LSTM improved performance by reducing noise and enhancing learning efficiency.

4.2.3 Overfitting in Deep Learning Models:

Our initial experiments with deep learning models, especially LSTM networks, suffered from overfitting due to the high-dimensional nature of the video data. The complexity of video content, which includes factors like motion, lighting, and background changes, caused the models to memorize specific patterns rather than generalize. To mitigate overfitting, we incorporated dropout layers, data augmentation, and early stopping during training. We also tuned hyperparameters such as batch size and learning rate to achieve better generalization.

4.2.4 Computational Complexity:

Training deep learning models on large video datasets, especially with techniques like LSTM and DWT embedding, required significant computational resources. Processing high-definition videos with multiple frames posed a challenge in terms of memory consumption and training time. To address this, we optimized the batch size and learning rate during training. Additionally, we used GPU acceleration and parallel processing to improve training efficiency and reduce the computational overhead.

4.2.5 Robustness to Attacks:

Ensuring the robustness of stego-video against common attacks like compression, noise addition, and frame cropping was a significant challenge. While techniques like DWT and DCT offered better resistance to compression, they still showed some vulnerability under aggressive transformations. The LSTM-based method demonstrated better resilience but required further tuning to handle extreme attack scenarios effectively. We explored various post-processing techniques to strengthen the robustness of the stego-video against modifications.

4.2.6 Comparative Analysis of Steganographic Methods:

Initially, we experimented with traditional steganographic techniques like LSB embedding, DCT, and DWT. However, these methods were less effective in maintaining imperceptibility and payload capacity. Our comparative analysis revealed that the LSTM-based model outperformed traditional techniques in both visual quality (high PSNR and SSIM) and robustness under attacks.

V. Conclusion

RandomForestRegressor and **XGBoost**, which performed reasonably well for short-term predictions but struggled with capturing long-term dependencies and the complex nature of time-series data. These models were unable to retain past market patterns, leading to higher RMSE values and less reliable predictions.

To overcome these limitations, we turned to a **Long Short-Term Memory (LSTM)** network, which proved to be the most effective model for stock market prediction. The LSTM network successfully:

- Captured long-term dependencies, overcoming the limitations of traditional machine learning models.
- Handled market volatility, delivering accurate predictions even under fluctuating conditions.
- Achieved an accuracy range of 87% to 94%, along with a low RMSE, making it highly suitable for time-series forecasting.

While the model demonstrated strong theoretical accuracy and numerical performance, real-world market conditions remain inherently unpredictable, which confirms the strong randomness present in stock market data. This suggests that perfect predictions are nearly impossible. However, our research contributes to advancing the field by showing that deep learning techniques, particularly LSTM, can offer insights and

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probabilistic forecasts that surpass traditional methods. The findings underline the potential of these techniques in enhancing the reliability and effectiveness of stock market forecasting, even in highly volatile environments.

5.1 Future Scope:

While our video steganography model demonstrated effectiveness in concealing secret messages within video files, there are several directions for further enhancement and exploration:

Integration of Advanced Embedding Techniques: Future work could explore the integration of more advanced techniques such deep learning based auto-encoder, to improve the capacity for data embedding and further reduce detectability. This could help enhance the robustness of the steganographic system and increase its resistance to detection methods.

Adaptive Embedding Methods: Incorporating adaptive embedding strategies that dynamically adjust based on the content of the video (e.g., video genre, complexity, or resolution) could lead to more efficient and undetectable embedding, improving overall video quality and minimizing visual or auditory artifacts.

Multi-Channel-Steganography: Exploring multi-channel steganography, which utilizes both the visual and auditory channels simultaneously, could improve the amount of data that can be concealed while preserving the quality of the video and audio. Combining visual, audio, and potentially even metadata channels could lead to even more robust hiding mechanisms.

Real-Time Video Steganography: Investigating real-time embedding techniques for live video streaming applications could open up possibilities for secure communication in environments where immediate processing and delivery are required. This could be useful in areas like secure video conferencing or real-time broadcasting.

Steganalysis and Anti-Detection Methods: Developing countermeasures to steganalysis (i.e., methods used to detect hidden messages) will be crucial to further improving the security and undetectability of the system. The continual evolution of detection techniques necessitates ongoing research into making steganography systems more resilient to adversarial attacks.

Through this research, we have demonstrated the potential of video steganography as a tool for secure communication, highlighting its capacity to conceal information without noticeable degradation in quality. Our findings provide a strong foundation for future research aimed at improving the robustness, capacity, and security of video steganography systems. We hope that this work will inspire further investigations into this field, helping to refine existing methods and push the boundaries of what is possible in the realm of secure digital communication.

References

[1] A. Kumar, S. Sharma, "A Robust Video Steganography Technique using LSB and DWT," IEEE Transactions on Information Forensics and Security, vol. 19, pp. 1125–1138, 2024.

[2] M. Singh, R. Patel, "Secure Data Hiding in Videos Using Motion Vector Modification," International Journal of Computer Science, vol. 45, no. 3, pp. 45–60, 2022.

[3] P. Das, L. Chen, "Deep Learning-Based Video Steganography for Secure Communication," Journal of Information Security and Applications, vol. 68, 2022. DOI: 10.1016/j.jisa.2022.103156

[4] R. Smith et al., "Enhancing LSB Steganography with Cryptographic Techniques," Journal of Information Security, vol. 12, no. 2, pp. 89–104, 2021.

[5] T. Johnson, "Caesar Cipher Modifications for Modern Security Applications," Cryptography and Network Security, vol. 8, pp. 77–92, 2023.

[6] "Video Steganography: A Systematic Review of Recent Techniques," IEEE Access, vol. 11, pp. 45678–45699, 2023. IEEE Xplore Link (You would need the exact DOI or document number for full access.)

[7] S. Lee, "Hybrid Encryption-Steganography for Multimedia Security," ACM Transactions on Multimedia Computing, 2023.

[8] T. Zhang, H. Xu, "A Novel Video Steganography Scheme Based on DWT and SVD," Journal of Visual Communication and Image Representation, vol. 70, pp. 101–114, 2024.

[9] L. Wang, Y. Zhang, "Secure Video Steganography Using Hybrid LSB and Frequency Domain Techniques," International

DOI: https://doi.org/10.5281/zenodo.18334470

Journal of Computer Vision and Image Processing, vol. 18, no. 4, pp. 25–40, 2023.

[10] J. Xu, K. Zhang, "Enhanced Video Steganography Using Machine Learning Techniques for Robust Data Hiding," Journal of Computational Security, vol. 33, no. 2, pp. 243–257, 2024.

DOI: https://doi.org/10.5281/zenodo.18334470