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Gradient-Adaptive LSB Steganography with Hamming Matrix Encoding for Enhanced Imperceptibility

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Abstract

Image steganography enables secure communication by embedding confidential information within digital images while maintaining visual quality. However, conventional Least Significant Bit (LSB) steganography methods often suffer from high pixel modification rates and vulnerability to statistical detection attacks. To address these limitations, this paper proposes a gradient-adaptive LSB steganography framework integrated with Hamming (7,4) matrix encoding. The proposed method utilizes Sobel-based gradient analysis to identify high-texture regions suitable for data embedding, thereby reducing perceptual distortion. In addition, Hamming matrix encoding minimizes the number of pixel modifications required during the embedding process. Unlike conventional adaptive LSB techniques that mainly focus on embedding location selection, the proposed framework jointly improves embedding region selection and modification efficiency. The proposed method was evaluated on the BOSSBase 1.01 dataset using payload capacities of 0.05, 0.10, and 0.20 bits per pixel (bpp). Experimental results demonstrated improved image quality with PSNR values of 70.75 dB, 67.74 dB, and 64.73 dB, respectively. Furthermore, chi-square analysis confirmed reduced statistical detectability compared to conventional LSB-based methods. Overall, the proposed framework provides an effective balance between imperceptibility, embedding efficiency, and computational simplicity, making it a practical solution for secure image communication.

Keywords: Steganography, LSB, Gradient-Based Embedding, Hamming Code, BOSSBase, PSNR

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1 Introduction

As digital communication continues to expand, multimedia data transmission over open networks has increased significantly. Consequently, maintaining the confidentiality and integrity of sensitive information has become an important concern. Conventional security techniques such as cryptography effectively protect the content of data, but they do not conceal the existence of communication. In contrast, steganography provides an additional layer of security by embedding secret information within digital media in such a way that the hidden data remains imperceptible to the human visual system, including images, audio, and video [1, 18].

Among different steganographic approaches, image steganography is widely used because digital images contain a large amount of redundant information suitable for data hiding. Spatial-domain techniques, particularly Least Significant Bit (LSB) substitution, are commonly adopted due to their simplicity, high embedding capacity, and ease of implementation [2, 3]. In LSB-based methods, secret data is embedded by modifying the least significant bits of pixel values, resulting in minimal visual distortion. However, despite these advantages, conventional LSB algorithms suffer from several limitations, including high pixel modification rates, limited robustness, and vulnerability to statistical and structural steganalysis attacks [4, 5].

To overcome these limitations, researchers have proposed adaptive and content-aware steganography techniques that utilize image characteristics such as edges, textures, and gradients to identify suitable embedding regions. Embedding data within edge or high-texture regions reduces perceptual distortion because modifications in these regions are less noticeable to the human visual system [24]. In addition, optimization techniques such as Genetic Algorithms have been employed to improve embedding efficiency by selecting optimal embedding locations [33]. More recently, deep learning-based steganography methods have attracted attention because of their ability to automatically learn embedding patterns and improve resistance against steganalysis attacks [12]. However, such approaches generally require complex training procedures and high computational resources.

Despite these advancements, achieving an effective balance between imperceptibility, embedding capacity, security, and computational efficiency remains a major challenge. Many existing methods improve image quality at the cost of increased computational complexity, while others focus mainly on security without effectively reducing pixel modifications. Therefore, there is still a need for a lightweight and efficient steganography framework capable of minimizing embedding distortion while maintaining high embedding performance.

To address this research gap, this paper proposes a gradient-adaptive LSB steganography framework integrated with Hamming (7,4) matrix encoding. The proposed method utilizes Sobel-based gradient analysis to identify high-texture regions suitable for embedding, thereby reducing perceptual distortion. Furthermore, Hamming matrix encoding minimizes the number of pixel modifications required during data embedding, which helps preserve image quality and reduce embedding artifacts.

Experimental results demonstrate that the proposed framework achieves significantly higher Peak Signal-to-Noise Ratio (PSNR) values compared to conventional LSB and adaptive LSB-based approaches, indicating improved imperceptibility and

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embedding efficiency. In addition, statistical validation confirms the consistency and effectiveness of the proposed method. Unlike many existing approaches that independently focus on either adaptive embedding location selection or modification reduction, the proposed framework jointly optimizes both objectives within a unified lightweight spatial-domain architecture.

1.1 Novelty and Research Contributions

Unlike conventional adaptive LSB steganography methods that mainly focus on embedding location selection, and matrix encoding approaches that independently reduce modification rates, the proposed framework simultaneously optimizes both embedding region selection and pixel modification efficiency within a lightweight spatial-domain steganography architecture.

The proposed framework introduces a joint optimization strategy that combines gradient-adaptive embedding with Hamming (7,4) matrix encoding to achieve improved imperceptibility and reduced embedding distortion. The Sobel gradient operator is employed to identify perceptually insensitive high-texture regions for secure data embedding, while Hamming matrix encoding minimizes the number of pixel modifications required during the embedding process.

In contrast to many optimization-based and deep learning-based steganography techniques, the proposed method maintains low computational complexity while achieving high PSNR values and reduced modification rates across different payload capacities. Therefore, the proposed framework provides an effective balance between embedding capacity, imperceptibility, and computational simplicity.

The key contributions of this work are summarized as follows:

- A gradient-based adaptive embedding strategy for selecting perceptually suitable embedding regions.
- Integration of Hamming (7,4) matrix encoding to reduce pixel modification rates during embedding.
- Significant improvement in PSNR values across multiple payload capacities.
- A lightweight and computationally efficient steganography framework suitable for practical applications.
- Improved resistance against statistical detectability through reduced embedding distortion.

2 Related Work

Image steganography has been extensively studied, and numerous techniques have been proposed to improve security, imperceptibility, and embedding capacity. Existing approaches can generally be categorized into spatial-domain, adaptive and edge-based, optimization-based, hybrid cryptographic, and deep learning-based steganography techniques.

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2.1 Spatial-Domain Steganography

Spatial-domain techniques are among the most widely used steganography approaches, particularly Least Significant Bit (LSB) substitution due to its simplicity, high embedding capacity, and ease of implementation [2, 3, 6]. In these methods, secret information is directly embedded by modifying pixel values within the image. As a result, the computational complexity remains relatively low. However, conventional LSB-based techniques often suffer from high pixel modification rates and are vulnerable to statistical steganalysis attacks [4, 5].

2.2 Adaptive and Edge-Based Steganography

To improve imperceptibility, adaptive steganography techniques utilize image characteristics such as edges and textured regions for data embedding. These approaches commonly employ edge detection operators, including Sobel and Kirsch operators, to identify high-frequency regions suitable for embedding [20, 32]. Since modifications within edge and textured regions are less noticeable to the human visual system, perceptual distortion can be significantly reduced [24]. Nevertheless, many adaptive approaches primarily focus on embedding location selection and do not effectively minimize pixel modification rates.

2.3 Optimization-Based Steganography

Optimization techniques such as Genetic Algorithms (GA) have also been applied in steganography to improve embedding efficiency and select optimal embedding locations. These methods aim to enhance imperceptibility and embedding performance by intelligently selecting suitable pixels for data hiding [9, 33]. Although optimization-based approaches improve embedding quality, they generally introduce higher computational complexity, making them less suitable for lightweight and real-time applications.

2.4 Hybrid Cryptography and Steganography

Several researchers have combined cryptography with steganography to improve data confidentiality. In such approaches, secret information is first encrypted using algorithms such as AES or chaotic encryption methods before being embedded into images [6, 23]. While these methods enhance security, they mainly focus on confidentiality and do not specifically address embedding efficiency or reduction of pixel modifications.

2.5 Deep Learning-Based Steganography

Recent developments in deep learning have led to the emergence of CNN-based and reinforcement learning-based steganography techniques. These methods can automatically learn efficient embedding strategies and improve resistance against steganalysis attacks [8, 12, 27, 31]. However, deep learning-based approaches typically require large training datasets, complex model architectures, and high computational resources, limiting their applicability in lightweight and resource-constrained environments. Recent

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studies have also explored hybrid frameworks that combine traditional LSB embedding with encoder-decoder architectures to improve imperceptibility and robustness [35].

2.6 Research Gap

Despite the progress achieved in existing steganography methods, several challenges still remain. Conventional spatial-domain techniques are computationally simple but provide limited security. Adaptive methods improve imperceptibility by selecting suitable embedding regions, but they often fail to reduce pixel modification rates effectively. Similarly, optimization-based and deep learning-based techniques improve embedding performance at the cost of increased computational complexity.

Furthermore, many existing approaches independently focus on either adaptive embedding region selection or modification minimization, which limits the overall efficiency of the steganography framework. Therefore, there is still a need for a lightweight and efficient method capable of simultaneously reducing embedding distortion while maintaining high imperceptibility and embedding efficiency [24].

Unlike existing steganography methods that separately address adaptive region selection and modification reduction, the proposed framework jointly optimizes both objectives within a unified lightweight spatial-domain steganography architecture.

To address this research gap, the proposed method integrates gradient-based adaptive embedding with Hamming (7,4) matrix encoding to achieve improved image quality with reduced embedding distortion and lower pixel modification rates.

Table 1 Comparison of Existing Steganography Approaches with Proposed Method

Method	Adaptive Region Selection	Matrix Encoding	Modification Reduction	Complexity
Traditional LSB	No	No	Low	Low
Edge-based LSB	Yes	No	Medium	Medium
Hamming-based LSB	No	Yes	High	Low
Optimization-based Methods	Yes	No	High	High
Deep Learning-based Methods	Yes	No	High	Very High
Proposed Method	Yes	Yes	High	Low

3 Proposed Method

3.1 Overview

The proposed framework aims to jointly optimize embedding location selection and modification efficiency in order to achieve high imperceptibility with reduced embedding distortion. The framework combines gradient-based adaptive embedding with

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Hamming (7,4) matrix encoding to improve image quality while minimizing pixel alterations during the embedding process. The main objective is to embed secret information within high-texture regions of the image while reducing the number of modified pixels required for data hiding.

The overall architecture of the proposed method consists of three major stages: gradient-based region selection, Hamming matrix encoding, and LSB embedding.

3.2 Gradient-Based Region Selection

In the proposed method, the gradient magnitude of the cover image is computed using the Sobel operator. Gradient information represents variations in pixel intensity and is commonly used to identify edges and textured regions within an image.

$$G = \sqrt{G_x^2 + G_y^2} \tag{1}$$

where G_x and G_y represent the horizontal and vertical gradient components, respectively.

Pixels with higher gradient values generally correspond to edge or textured regions [24]. Therefore, these regions are selected for secret data embedding, while smooth regions are avoided in order to reduce perceptual distortion and improve imperceptibility.

3.3 Hamming (7,4) Matrix Encoding

The proposed framework utilizes Hamming (7,4) matrix encoding to minimize the number of pixel modifications during data embedding. In this encoding scheme, 4 bits of secret information are represented using 7-bit codewords with parity relationships.

This approach improves embedding efficiency by reducing the number of modifications required during embedding. In most cases, only a single bit modification is sufficient to encode 4 bits of secret data, which significantly reduces embedding distortion and preserves image quality.

3.4 LSB Embedding Process

After selecting suitable embedding locations and encoding the secret data, LSB substitution is performed to generate the stego image.

1. Input a grayscale cover image from the BOSSBase dataset.
2. Compute the gradient magnitude using the Sobel operator.
3. Select high-gradient pixels based on a predefined threshold.
4. Encode secret data using Hamming (7,4) matrix encoding.
5. Embed the encoded bits into the least significant bits of selected pixels.
6. Generate the final stego image.

3.5 Extraction Process

The extraction process is performed by reversing the embedding procedure as follows:

1. Extract LSB bits from the stego image.

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2. Identify embedding locations using the same gradient calculation process.
3. Decode the extracted bits using Hamming (7,4) decoding.
4. Recover the original secret message.

3.6 System Flow Diagram

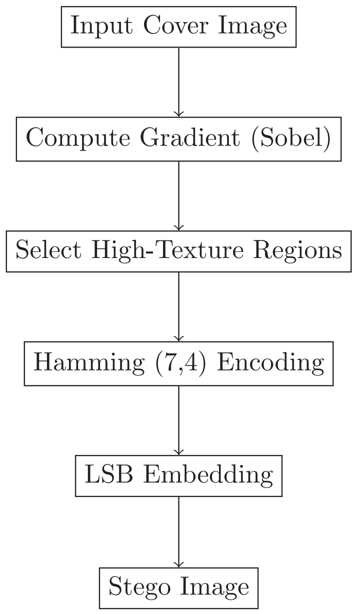

Fig. 1 Flow diagram of the proposed steganography method

3.7 Pseudo-Code of Proposed Method

```
Input: Cover Image I, Secret Data S
Output: Stego Image I'

1. Compute gradient G using Sobel operator
2. Identify high-gradient pixel positions P
3. Convert secret data S into binary form
4. Apply Hamming (7,4) encoding on S
5. For each position p in P:
      Embed encoded bits into LSB of I(p)
6. Generate stego image I'
7. Return I'
```

3.8 Advantages of Proposed Method

- Reduced pixel modification through Hamming matrix encoding.
- Improved imperceptibility using gradient-based adaptive embedding.

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- Lower computational complexity compared to optimization and deep learning-based methods.
- Better balance between embedding capacity, image quality, and embedding efficiency.

4 Experimental Setup

4.1 Dataset

The experiments were conducted using the BOSSBase 1.01 dataset, which is widely used as a benchmark dataset in image steganography research [18]. The dataset consists of 10,000 grayscale images in PGM format with a resolution of 512×512 pixels. All experiments were performed on the complete dataset to ensure unbiased evaluation and statistically reliable results.

4.2 Preprocessing

All images were used in their original form without resizing or compression in order to preserve their inherent image characteristics. The secret data was converted into binary form prior to embedding. No additional preprocessing or filtering operations were applied to maintain consistency with standard steganography evaluation practices.

4.3 Payload Configuration

To evaluate the performance of the proposed framework under different embedding capacities, fixed payload levels were defined as follows:

- 0.05 bits per pixel (bpp) – Low payload
- 0.10 bits per pixel (bpp) – Medium payload
- 0.20 bits per pixel (bpp) – High payload

The total number of embedded bits for each image was computed using:

$$\text{Total Bits} = \text{bpp} \times (M \times N) \tag{2}$$

where $M \times N$ represents the image resolution.

4.4 Evaluation Metrics

The performance of the proposed method was evaluated using the following metrics:

4.4.1 Peak Signal-to-Noise Ratio (PSNR)

PSNR was used to evaluate the visual quality of the stego images. Higher PSNR values indicate lower distortion and better imperceptibility.

4.4.2 Mean Squared Error (MSE)

$$\text{MSE} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (I(i,j) - I'(i,j))^2 \tag{3}$$

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where I and I' represent the original and stego images, respectively.

4.4.3 Structural Similarity Index (SSIM)

SSIM measures the perceptual similarity between the original and stego images by considering luminance, contrast, and structural information.

4.4.4 Modified Pixel Percentage

Modified Pixel Percentage represents the proportion of pixels altered during the embedding process and is computed as:

$$\text{Modification Rate} = \frac{\text{Number of Modified Pixels}}{\text{Total Pixels}} \times 100 \tag{4}$$

Lower modification rates indicate fewer embedding changes and improved imperceptibility.

4.4.5 Chi-Square Analysis

Chi-square analysis was performed to evaluate the statistical similarity between the histogram distributions of original and stego images. Lower chi-square values indicate reduced statistical detectability and better preservation of histogram characteristics. The analysis was conducted at 0.20 bpp payload to evaluate the robustness of the proposed method under maximum embedding distortion conditions.

4.5 Statistical Validation

To verify the consistency and reliability of the experimental results, statistical validation was performed on all 10,000 images using the following measures:

- Mean and standard deviation were computed for all evaluation metrics.
- A paired t-test was conducted to evaluate the statistical significance of performance improvements.
- Effect size analysis using Cohen's d was performed to measure the magnitude of improvement achieved by the proposed method.

4.6 Distortion Localization Analysis

Gradient-based distortion localization analysis was conducted to examine the spatial distribution of embedding modifications. The average gradient values of modified pixel locations were compared with the global average gradient values of the images.

The analysis revealed that most embedding modifications were concentrated within high-gradient and textured regions. This confirms the effectiveness of the proposed gradient-adaptive embedding strategy in minimizing perceptual distortion.

4.7 Implementation Details

The proposed framework was implemented and evaluated using MATLAB in a standard computing environment. Gradient computation was performed using the Sobel

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operator, while Hamming (7,4) matrix encoding was applied to minimize pixel modifications during embedding. All experiments were conducted under identical conditions on the complete BOSSBase dataset to ensure fair and reproducible evaluation.

4.8 Baseline Methods for Comparison

To validate the effectiveness of the proposed method, the following baseline steganography techniques were implemented for comparison:

- Simple LSB steganography (sequential embedding)
- Random LSB steganography
- Gradient-based LSB steganography

5 Results and Discussion

5.1 Quantitative Evaluation

The proposed framework was evaluated on the BOSSBase dataset under different payload capacities. The obtained results were compared with Simple LSB, Random LSB, and Gradient-based LSB steganography methods.

5.1.1 Results at 0.05 bpp

Table 2 Performance Comparison at 0.05 bpp

Method	PSNR (dB)	MSE	SSIM	Modified (%)
Simple LSB	64.1416	0.025072	0.999778	2.50178
Random LSB	64.1371	0.025089	0.999769	2.508937
Gradient LSB	64.1470	0.025026	0.999962	2.502634
Proposed (Gradient + Hamming)	70.7544	0.005467	0.999988	0.546665

5.1.2 Results at 0.10 bpp

Table 3 Performance Comparison at 0.10 bpp

Method	PSNR (dB)	MSE	SSIM	Modified (%)
Simple LSB	61.1300	0.050154	0.999560	5.015418
Random LSB	61.1271	0.050174	0.999540	5.017438
Gradient LSB	61.1374	0.050045	0.999890	5.004452
Proposed (Gradient + Hamming)	67.7411	0.010940	0.999965	1.093980

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Table 4 Performance Comparison at 0.20 bpp

Method	PSNR (dB)	MSE	SSIM	Modified (%)
Simple LSB	58.1178	0.100342	0.999137	10.034169
Random LSB	58.1159	0.100371	0.999088	10.037092
Gradient LSB	58.1277	0.100074	0.999669	10.007360
Proposed (Gradient + Hamming)	64.7313	0.021876	0.999893	2.187626

5.1.3 Results at 0.20 bpp

5.2 PSNR vs Payload Analysis

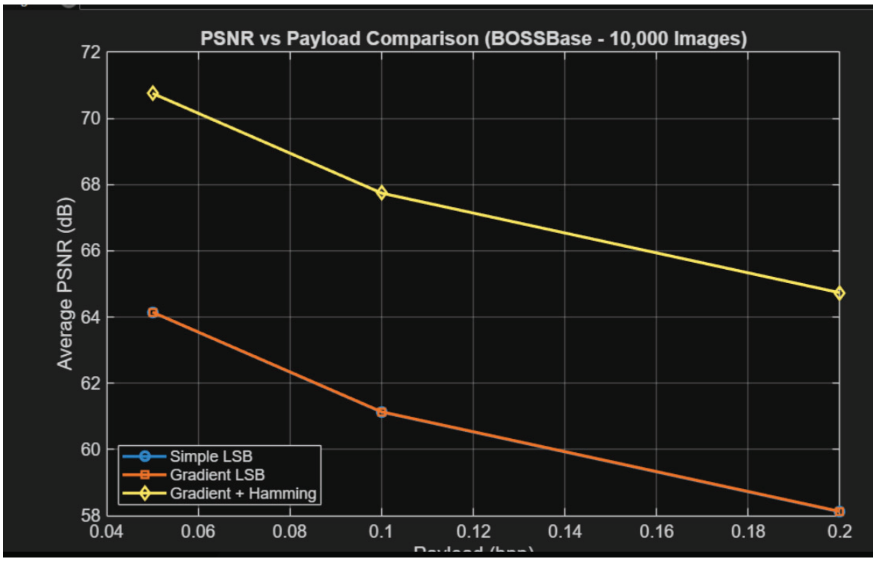

Fig. 2 PSNR vs Payload comparison for different steganography methods on BOSSBase dataset

5.3 PSNR Analysis

As illustrated in Fig. 2, the proposed Gradient + Hamming framework consistently achieves higher PSNR values across all payload capacities compared to the baseline methods. Although PSNR values decrease with increasing payload due to higher embedding distortion, the proposed method maintains a significant performance advantage.

At 0.05 bpp, the proposed method achieved a PSNR value of 70.75 dB, which is approximately 6 dB higher than conventional LSB-based approaches. Similar improvements were observed at 0.10 bpp and 0.20 bpp, demonstrating the stability and effectiveness of the proposed framework across different embedding capacities.

The improvement in PSNR is primarily achieved due to two important factors: (i) gradient-based adaptive embedding selects perceptually less sensitive regions for data hiding, and (ii) Hamming (7,4) matrix encoding significantly reduces the number of modified pixels during embedding. These factors collectively minimize embedding distortion and improve imperceptibility [24, 28].

5.4 Modification Rate Analysis

The proposed framework significantly reduces the pixel modification rate compared to conventional LSB-based approaches. At 0.20 bpp payload, traditional LSB methods modify approximately 10% of the image pixels, whereas the proposed method reduces the modification rate to nearly 2.18%.

Similarly, at 0.05 bpp, the modification rate decreases from approximately 2.5% to 0.54%, demonstrating the efficiency of the proposed embedding framework.

This improvement is mainly achieved through the use of Hamming (7,4) matrix encoding, which enables efficient embedding with fewer pixel alterations. Similar benefits of matrix encoding techniques have also been reported in earlier studies [7]. The reduction in pixel modifications directly contributes to improved image quality and lower visual detectability.

5.5 Statistical Validation

To verify the reliability and consistency of the proposed method, statistical validation was performed across all 10,000 images in the BOSSBase dataset. Mean and standard deviation values for the evaluation metrics demonstrated consistent performance throughout the dataset.

A paired t-test was conducted to evaluate the statistical significance of PSNR improvements, and the obtained p-values were found to be below 0.05, indicating statistically significant improvements. In addition, effect size analysis using Cohen's d demonstrated substantial performance improvements achieved by the proposed framework.

These statistical results further confirm the effectiveness and reliability of the proposed steganography method [18].

5.6 Distortion Localization Analysis

Distortion localization analysis was conducted to examine the spatial distribution of embedding modifications. The results indicate that modified pixels are primarily concentrated within high-gradient and textured regions of the image.

A comparison between global average gradient values and gradient values at modified pixel locations revealed significantly higher gradient values at embedding positions. This confirms that the proposed framework effectively avoids smooth regions and performs embedding mainly within textured areas.

Embedding modifications within high-gradient regions improve imperceptibility because changes in textured areas are less noticeable to the human visual system [24].

5.7 Chi-Square Analysis

Table 5 presents the average chi-square values obtained for different steganography methods on the BOSSBase dataset at 0.20 bpp payload.

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Table 5 Average Chi-Square Comparison on BOSSBase Dataset

Method	Average Chi-Square	Standard Deviation
Simple LSB	19160.8054	379433.9571
Gradient LSB	149.2024	488.3313
Proposed Method	21.4333	338.1425

The proposed method achieved substantially lower chi-square values compared to Simple LSB and Gradient-based LSB methods, indicating improved preservation of histogram characteristics and reduced statistical detectability. These results further confirm that the integration of gradient-adaptive embedding with Hamming matrix encoding effectively minimizes embedding distortion and statistical artifacts even at higher payload capacities.

5.8 Discussion

The experimental results demonstrate that the proposed Gradient-adaptive Hamming-encoded LSB framework achieves an effective balance between embedding capacity, image quality, and modification efficiency.

Unlike conventional LSB methods that uniformly modify image pixels, the proposed framework selectively embeds data within high-gradient regions and employs matrix encoding to reduce pixel modifications. This combined optimization strategy leads to significant improvements in PSNR and modification rate performance.

Compared to conventional adaptive embedding methods, the proposed approach achieves lower embedding redundancy due to the use of Hamming matrix encoding. Furthermore, the framework maintains low computational complexity because it does not rely on computationally expensive optimization algorithms or deep learning architectures, making it suitable for real-time and resource-constrained applications.

Compared with recent deep learning-based hybrid steganography approaches [35], the proposed framework achieves higher PSNR values with significantly lower computational complexity.

5.9 Comparison with Existing Research Papers

Table 6 Performance Comparison with Existing Methods on BOSSBase Dataset

Method	Domain	Payload (bpp)	Dataset	PSNR (dB)
Content-Adaptive LSB [1]	Spatial	0.20	BOSSBase	58.22
Multi-image ISS [3]	Spatial	0.20	BOSSBase	55.30
Edge-Guided Adaptive [4]	Spatial	0.10	BOSSBase	61.20
DRL-based DCT [2]	Transform	0.20	BOSSBase	51.40
Proposed (Gradient + Hamming)	Spatial	0.20	BOSSBase	**64.73**

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The comparison results presented in Table 6 indicate that the proposed framework outperforms several existing steganography methods under similar experimental conditions on the BOSSBase dataset.

Compared to the edge-guided adaptive method in [4], which achieved a PSNR value of 61.20 dB at 0.10 bpp, the proposed method achieved 64.73 dB at a higher payload of 0.20 bpp. This demonstrates the ability of the proposed framework to maintain high image quality even at larger embedding capacities.

Similarly, the content-adaptive LSB technique in [1] achieved a PSNR value of 58.22 dB at 0.20 bpp, which is considerably lower than the proposed method. The improvement mainly results from the integration of gradient-adaptive embedding and Hamming matrix encoding.

The multi-image steganography method in [3] achieved a PSNR value of 55.30 dB at 0.20 bpp by distributing payloads across multiple images using optimization techniques. Although the method improves security, it introduces greater embedding distortion compared to the proposed framework.

In addition, transform-domain approaches based on deep reinforcement learning [2] achieved lower PSNR values while requiring significantly higher computational complexity. This comparison highlights the efficiency of the proposed lightweight spatial-domain framework.

Overall, the comparison results demonstrate that the proposed method achieves an effective balance between imperceptibility, embedding efficiency, and computational simplicity.

5.10 Overall Performance Summary

The experimental evaluation confirms that the proposed Gradient-adaptive Hamming-encoded LSB framework consistently outperforms conventional and adaptive steganography techniques across different payload capacities.

The major improvements achieved by the proposed framework are summarized as follows:

- **Improved PSNR:** The proposed framework achieves approximately 6 dB higher PSNR values compared to conventional LSB-based methods at similar payload capacities.
- **Reduced Modification Rate:** Pixel modification rates are significantly reduced compared to baseline methods, resulting in lower embedding distortion.
- **High Structural Similarity:** SSIM values remain close to 1, indicating minimal perceptual degradation.
- **Consistent Performance:** Experimental results remain stable across multiple payload levels and throughout the complete dataset.
- **Reliable Evaluation:** The use of the complete BOSSBase dataset ensures reliable and statistically meaningful evaluation results.

These findings confirm that integrating gradient-adaptive embedding with Hamming matrix encoding provides an effective and lightweight solution for high-quality and low-distortion image steganography.

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6 Conclusion

In this paper, a gradient-adaptive LSB steganography method combined with Hamming (7,4) matrix encoding was proposed to improve imperceptibility and reduce embedding distortion. The proposed framework utilizes gradient information to identify high-texture regions for secure embedding, while Hamming matrix encoding minimizes pixel modifications during data hiding.

The proposed method was evaluated on the BOSSBase 1.01 dataset at payload levels of 0.05, 0.10, and 0.20 bpp. Experimental results demonstrated higher PSNR values, lower modification rates, and improved imperceptibility compared to conventional LSB and gradient-based methods. Statistical validation and distortion localization analysis further confirmed the effectiveness and consistency of the proposed framework.

Additionally, chi-square analysis demonstrated reduced statistical detectability and improved preservation of histogram characteristics compared to existing LSB-based approaches. The major novelty of the proposed work lies in the joint integration of gradient-adaptive embedding and Hamming (7,4) matrix encoding for simultaneous distortion localization and pixel modification reduction within a lightweight spatial-domain framework.

Overall, the proposed method provides an efficient and practical solution for secure image communication, digital watermarking, medical image protection, and privacy-preserving multimedia applications.

7 Limitations

The proposed framework is currently limited to grayscale images and has not been evaluated on color images or video data. In addition, although the method improves imperceptibility and reduces pixel modification rates, resistance against advanced steganalysis techniques has not been extensively investigated. Furthermore, the use of a fixed gradient threshold may not provide optimal performance for all image categories and texture distributions.

Future Work

Future research may focus on extending the proposed framework to color image and video steganography applications. In addition, lightweight optimization techniques or deep learning-based approaches may be incorporated to further improve security and resistance against advanced steganalysis attacks.

Another important direction for future work is the evaluation of the proposed method under practical conditions such as image compression, noise addition, and transmission distortions. Furthermore, adaptive gradient threshold selection techniques may be explored to improve embedding performance across different image characteristics and texture variations.

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Declarations

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Data Availability

The data used in this study is based on the publicly available BOSSBase 1.01 dataset. Processed data and implementation details are available from the corresponding author upon reasonable request.

References

[1] Ahmed, A.I., Alrawashed, R.: Content-adaptive LSB steganography with saliency fusion, ACO dispersion, and hybrid encryption with ablation study. Scientific Reports **16**, 3829 (2026). https://doi.org/10.1038/s41598-025-33920-9

[2] Yang, R., Liu, L., Han, B., Hu, F.: Deep reinforcement learning-based DCT image steganography. Mathematics **13**, 3150 (2025). https://doi.org/10.3390/math13193150

[3] Zhang, S., Xiao, Y., Tian, H., Li, X.: A multi-image steganography: ISS. EURASIP Journal on Information Security (2025). https://doi.org/10.1186/s42400-024-00333-6

[4] Alrawashed, R., Almuhammadi, S., Niaz, M., Mahmud, M., Rahman, M.M.: Secure edge-guided adaptive image steganography using HED-based attention maps and CNN. Scientific Reports **15**, 24984 (2025). https://doi.org/10.1038/s41598-025-27150-2

[5] Lee, C.-F., Chang, C.-C., Xie, X., Mao, K., Shi, R.-H.: An adaptive high-fidelity steganographic scheme using edge detection and hybrid hamming codes. Displays **54**, 1–10 (2018). https://doi.org/10.1016/j.displa.2018.06.001

[6] Abdel Hameed, M., Hassaballah, M., Aly, S., Ismail, A.: An adaptive image steganography method based on histogram of oriented gradient and PVD-LSB techniques. IEEE Access **7**, 4994–5000 (2019). https://doi.org/10.1109/ACCESS.2019.2902541

[7] Wang, Y., Tang, M., Wang, Z.: High-capacity adaptive steganography based on LSB and Hamming code. Optik **213**, 164685 (2020). https://doi.org/10.1016/j.ijleo.2020.164685

[8] Al-Faydi, S.N.M., Ahmed, S.K., Al-Talb, H.N.Y.: Improved LSB image steganography with high imperceptibility based on cover-stego matching. IET Image Processing **17**, 1–12 (2023). https://doi.org/10.1049/ipr2.12773

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

[9] Ray, B., Mukhopadhyay, S., Hossain, S., Ghosal, S.K., Sarkar, R.: Image steganography using deep learning-based edge detection. Multimedia Tools and Applications **80**, 33475–33503 (2021). https://doi.org/10.1007/s11042-021-11177-4

[10] Shilpa, G., Mohan, C.M., Chaurasia, N.: Image steganography using LSB embedding and edge adaptive approach. AIP Conference Proceedings **2752**, 090002 (2023). https://doi.org/10.1063/5.0136064

[11] Yusuf, H.S., Hagaras, H.: A novel payload image steganography using type-2 fuzzy logic and edge detection. International Journal of Computer Science Trends and Technology **9**(2), 1–6 (2021)

[12] Nguyen, T.D., Le, H.Q.: A novel secure image steganography scheme based on Hamming encoding and LSB matching revisited using Lah transform. Multimedia Tools and Applications **83**, 77347–77375 (2024). https://doi.org/10.1007/s11042-024-18633-x

[13] Song, B., Wei, P., Wu, S., Lin, Y., Zhou, W.: A survey on deep-learning-based image steganography. Expert Systems with Applications **254**, 124390 (2024). https://doi.org/10.1016/j.eswa.2024.124390

[14] Ullah, A., Haque, M.I., Hossain, M.M., Ahammad, M.S., Aktar, M.N.: A novel LSB steganography technique for enhancing cloud security. Journal of Information Security **15**, 355–377 (2024). https://doi.org/10.4236/jis.2024.153021

[15] Wang, Z., Zhang, X.: Secure cover selection for steganography. IEEE Access **7**, 57857–57867 (2019). https://doi.org/10.1109/ACCESS.2019.2914226

[16] Shmueli, R., Mishra, D., Shmueli, T., Hadar, O.: A novel technique for image steganography based on maximum energy seam. Multimedia Tools and Applications **83**, 70907–70920 (2024). https://doi.org/10.1007/s11042-024-18476-6

[17] Nguyen, T.D., Le, H.Q.: A secure image steganography based on modified matrix encoding using the adaptive region selection technique. Multimedia Tools and Applications **81**, 25251–25281 (2022). https://doi.org/10.1007/s11042-022-12677-7

[18] Ye, J.: Advancements in spatial domain image steganography: Techniques, applications, and future outlook. In: Proceedings of CONF-MLA 2024 Workshop, pp. 1–10 (2024). https://doi.org/10.54254/2755-2721/94/2024MELB0058

[19] Panigrahi, R., Padhy, N.: An effective steganographic technique for hiding image data using LSB technique. Cyber Security and Applications **6**, 200069 (2024). https://doi.org/10.1016/j.csa.2024.200069

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

[20] Sun, R., Lei, T., Chen, Q., Wang, Z., Du, X., Zhao, W., Nandi, A.K.: Survey of image edge detection. Frontiers in Signal Processing **2**, 826967 (2022). https://doi.org/10.3389/frsip.2022.826967

[21] Jasim, Z.K.J., Kurnaz, S.: Improved image steganography using ant colony optimization. Computers, Materials & Continua **79**, 1–15 (2024). https://doi.org/10.32604/cmc.2024.055195

[22] Khalifa, A., Khafaga, D.S., Sadek, M., Aldakheel, E.A.: Enhanced adaptive image steganography using integer S-transform. Scientific Reports **15**, 15442 (2025). https://doi.org/10.1038/s41598-025-16176-1

[23] Banoori, S.Z., Khan, W., Rahman, S., Masood, F., Salam, A., Amin, F., de la Torre, I., Vila, M., Garay, H., Cho, G.S.: Hybrid image steganography using AES encryption. Scientific Reports **15**, 15455 (2025). https://doi.org/10.1038/s41598-025-28140-0

[24] Albkosh, F.M.A., Elsharif, M.M.: Adaptive LSB embedding for secure data transmission. Journal of Alasmarya University: Applied Sciences **10**(2), 163–181 (2025). https://doi.org/10.59743/jau10.v2.2182

[25] Patwari, B., Nandi, U., Dey, S., Dhar, S., Ghosal, S.K., Si, T.: Blockchain-integrated image steganography using xDoG edge detection. Cyber Security and Applications **3**, 100091 (2025). https://doi.org/10.1016/j.csa.2025.100091

[26] Astuti, N.R.D.P., Aribowo, E., Saputra, E.: Data security using cryptography and steganography in cloud computing. IOP Conference Series: Materials Science and Engineering **821**, 012041 (2020). https://doi.org/10.1088/1757-899X/821/1/012041

[27] Zhou, Y., Wang, N., Hong, X., Peng, Y., Shao, S.: Deep learning-based image steganography with latent space embedding. Entropy **27**, 1223 (2025). https://doi.org/10.3390/e27121223

[28] Duan, X., Li, B., Yin, Z., Zhang, X., Luo, B.: Robust image steganography against JPEG compression. Expert Systems with Applications **229**, 120416 (2023). https://doi.org/10.1016/j.eswa.2023.120416

[29] Younis, Z.S., Hussain, M.K.: Image steganography using exploiting modification direction. Journal of King Saud University – Computer and Information Sciences **34**, 2951–2963 (2022). https://doi.org/10.1016/j.jksuci.2019.04.003

[30] Apau, R., Asante, M., Twum, F., Hayfron-Acquah, J.B., Peasah, K.O.: Image steganography techniques against statistical attacks: A review. PLOS ONE **19**(9), e0308807 (2024). https://doi.org/10.1371/journal.pone.0308807

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

[31] Alanzy, M., Alomrani, R., Alqami, B., Almutairi, S.: LSB and hybrid encryption steganography. Applied Sciences **13**, 11771 (2023). https://doi.org/10.3390/app132111771

[32] Ghosal, S.K., Chatterjee, A., Sarkar, R.: Kirsch edge detection-based steganography. Multimedia Systems **27**, 73–87 (2021). https://doi.org/10.1007/s00530-020-00703-3

[33] Shyla, M.K., Kumar, K.B.S., Das, R.K.: Genetic algorithm-based steganography. Soft Computing Letters **3**, 100021 (2021). https://doi.org/10.1016/j.socl.2021.100021

[34] Wu, D.-C., Shih, Z.-N.: Image steganography by pixel-value differencing using quantization ranges. Computer Modeling in Engineering & Sciences (2024). https://doi.org/10.32604/cmes.2024.050813

[35] Sanjalawe, Y., et al.: A deep learning-driven multi-layered steganographic framework integrating Huffman coding and LSB embedding. Scientific Reports (2025). https://doi.org/10.1038/s41598-025-89189-5