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DYNAMIC RANGE OPTIMIZATION FOR REVERSIBLE DATA HIDING WITH INTENSITY-BASED EMBEDDING

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Abstract

Reversible data hiding is a technique that enables the recovery of the original media after the hidden data has been extracted. This feature is crucial in scenarios where any permanent alteration to the cover media is unacceptable. Examples of such applications include law forensics, satellite imagery, medical imaging, and cloud data management. In these fields, preserving the integrity of the original media is essential for accurate analysis and decision-making. Current advanced RDH approaches typically embed extra information into the cover media without taking pixel intensities into account. This uniform embedding strategy often leads to poor visual quality in the modified media, as the process does not differentiate between regions of varying sensitivity or intensity within the image.

In this work, the dynamic range of cover images is utilized to embed additional data based on pixel intensities. The proposed method involves dividing the cover image into two segments: part A and part B. Part A serves as the area for reversible data embedding, while part B is designated for storing the least significant bits of the pixels in part A.

The LSBs in part A are vacated according to predefined ranges that align with the human visual system and Weber's law. These extracted LSBs are then reversibly stored in part B using a histogram shifting-based RDH technique. This structured approach ensures that the embedding process is both reversible and minimally intrusive.

Upon reception, the process begins with the extraction of the additional data from part A. Subsequently, the hidden LSB stream in part B is retrieved, enabling the restoration of the original pixels in part A. This two-step extraction guarantees the reversibility of the embedding process.

Experimental evaluations conducted on a publicly available image dataset reveal that the proposed RDH methods achieve high embedding rates while maintaining low distortion in the modified images. Furthermore, the new approach demonstrates superior performance compared to existing state-of-the-art RDH techniques.

Introduction

The swift proliferation of digital technologies has fundamentally transformed the methodologies through which information is shared and stored. The transmission of sensitive data, including monetary transactions, medical records, and classified government data, necessitates a paramount focus on security measures. Encryption methodologies, although proficient in protecting information, frequently attract attention because of the unintelligible ciphertext they produce [1]. This renders such data susceptible to exploitation by attackers. Reversible Data Hiding (RDH) represents a distinct methodology that effectively embeds sensitive information within a cover medium, such as an image, while simultaneously assuring the flawless restoration of the original medium post data extraction. The dual capability of RDH makes it particularly significant for applications in which the preservation of data confidentiality and the assurance of content integrity are crucial [2].

Initial RDH methods relied on techniques like histogram shifting and prediction-error expansion. Although these methodologies effectively reduced distortions and preserved data integrity, they frequently encountered challenges in achieving an optimal equilibrium between embedding capacity and visual quality [3]. In the field of medical imaging, even minor aberrations in diagnostic images can result in incorrect diagnoses, thereby emphasizing the critical necessity for high perceptual fidelity. In the context of copyright protection, the embedded watermark must remain imperceptible [4]. This requirement serves to preserve the aesthetic value of the media while simultaneously enabling the authentication of ownership. The challenges presented highlight the shortcomings of conventional RDH methodologies in meeting contemporary requirements [5] [6]. This research presents an adaptive reversible data hiding (RDH) technique that utilizes pixel intensity ranges to dynamically modify the embedding process. The proposed method enhances data security by segmenting the image into distinct embedding and storage regions. This approach facilitates the embedding of sensitive information in a manner that is compatible with human visual perception, thereby minimizing the potential for observable distortions. A greater number of bits are allocated to both low and high intensity ranges, where variations are less noticeable. In contrast, a reduced number of bits are assigned to mid-intensity ranges to mitigate the occurrence of artifacts. This innovative methodology markedly improves embedding capacity alongside visual quality, attaining rates that surpass 1 bit per pixel (bpp) while sustaining a PSNR greater than 40 dB. This adaptive technique diverges from conventional methods that utilize uniform embedding strategies throughout the entire image, instead adapting the embedding process to align with the specific characteristics of the content. The integration of perceptual models, such as Weber's law, guarantees that the variations are not discernible to the human eye [7]. The reversible characteristic of the technique ensures that the original image can be accurately reconstructed, making it appropriate for critical applications including secure communication, medical diagnostics, and digital watermarking. In summary, the proposed adaptive RDH method addresses the limitations of existing techniques by introducing a dynamic, perceptually optimized embedding strategy. Its ability to balance high-capacity embedding with superior visual quality makes it a robust solution for the growing challenges in data security and content preservation.

Related Work

The underlying motivation of RDH comes from the work on lossless image authentication and reversible watermarking in early work. Fridrich et al. proposed the notion of an invertible authentication scheme, which showed that a watermarking scheme can be implemented without convincing contamination of the covering signal [1]. The area took off when Tian proposed the Canonical Difference Expansion (DE) scheme in 2003, a simple mathematical idea showing how to embed reversibly by increasing pixel differences between adjacent pixels [2].

Subsequently, RDH research developed simple-difference methods to complex adaptive, predictive, as well as deep learning–based techniques. Some important surveys have been done on this process, e.g., Zhang et al.'s comprehensive survey for reversible data hiding on uncompressed images [3] and Shi et al.'s influential two-decade retrospective [4]. These works highlight the variety of RDH algorithms, including histogram shift, prediction error expansion, pixel value ordering, integer transform, CNN based predictor and encrypted domain RDH and multi-histogram modification. Histogram Shifting was introduced by Ni et al. [5] as a distortion-limited alternative to DE. HS relies on the statistical distribution of pixel intensities or prediction errors. The idea is to identify peak bins (the most frequent values) and zero bins (values absent from the histogram). Histogram shifting is advantageous due to its low distortion and minimal overhead. Over time, researchers developed more sophisticated HS-based frameworks. Li et al. provided a general theoretical foundation for HS in RDH [6], while Li et al. later introduced 2D histogram modification for better efficiency [7]. Wang et al. proposed recursive histogram modification, establishing an equivalence between histogram shifting and lossless compression [8]. Prediction-Error Expansion builds upon DE by applying expansion not to raw pixel differences but to *prediction residuals*, thereby increasing embedding opportunities and reducing distortion. First formalized by Thodi and Rodriguez [9], PEE predicts each pixel using a neighboring context (e.g., causal or cross patterns) and uses the resulting error value to embed data.

Pixel Value Ordering (PVO) was introduced by Li et al. [10], proposing a clever mechanism in which each block is sorted, and the minimum and maximum pixel values are used for embedding. This approach exploits local smoothness: in smooth regions, adjacent pixel values are highly correlated, allowing efficient embedding. PVO evolved into PPVO (Prediction Pixel-Value Ordering), where prediction is combined with ordering to enhance accuracy and embedding rate [11].

Integer transforms, particularly the Generalized Integer Transform (GIT) proposed by Alattar [12] and extended by later researchers [13, 14, 15], offer a powerful mechanism for reversible embedding. They ensure invertibility and allow multi-pixel expansion within small pixel groups.

Multiple Histogram Modification (MHM) is one of the most powerful trends in recent RDH research. Rather than using a single histogram of pixel values or prediction errors, MHM decomposes the image into multiple contextual subsets, each with its own histogram. This increases the number of peak bins, thereby enlarging embedding capacity. Several notable contributions include: He et al. proposed adaptive multiple histogram modification for robust embedding [16], Zhang et al. extended this concept to multi-histogram contrast-enhanced methods [17], Wang et al. formalized a generalized MHM framework with theoretical guarantees [18], Ma et al. introduced fast expansion-bin determination to reduce computational overhead [19] and Qi et al. presented optimal MHM via rate-distortion optimization [20].

Content-adaptive RDH represents a significant evolutionary step beyond static global embedding strategies. These methods tailor the embedding rules based on local complexity, edge strength, brightness, or structural properties of the image. Pan et al. and Weng et al. [21, 22] explored complexity-aware PVO and multi-histogram embedding, demonstrating that adaptive region selection can significantly improve the PSNR–capacity trade-off. Human Visual System models, such as Weber's law and contrast sensitivity functions, have been increasingly used to guide embedding decisions. Relevant works include:

- Automatic brightness-preserving contrast enhancement [23]
- RDH with HVS-guided PVO [24]

These methods exploit the fact that human perception is less sensitive to changes in high-intensity or low-luminance regions—an insight central to the intensity-based strategy used in the proposed research.

Proposed Intensity based RDH Method

In this section, present methodology of the proposed embedding and extraction RDH method. The flow diagram of the proposed RDH method is illustrated in Figure 1. There are two primary components of the flow diagram: the data hider and the receiver. Pre-processing is done on the cover image to make space for data embedding later. The pre-processing stage separates the cover image into two sections, A and B. The data hider is given access to the pre-processed cover image. Additional data is embedded by the data hider into the part A of the processed image LSBs that were left empty in the preceding stage. The authentic recipient, who handles data extraction and the recovery of the original cover image, receives the marked image. After the designated image has been post-processed to separate it into parts A and B, data is extracted of part A. By extracting the hidden data from part B and insert it in part A, the original image is recovered. After part A's data is extracted from part B, part B is also restored because the data were embedded reversibly.

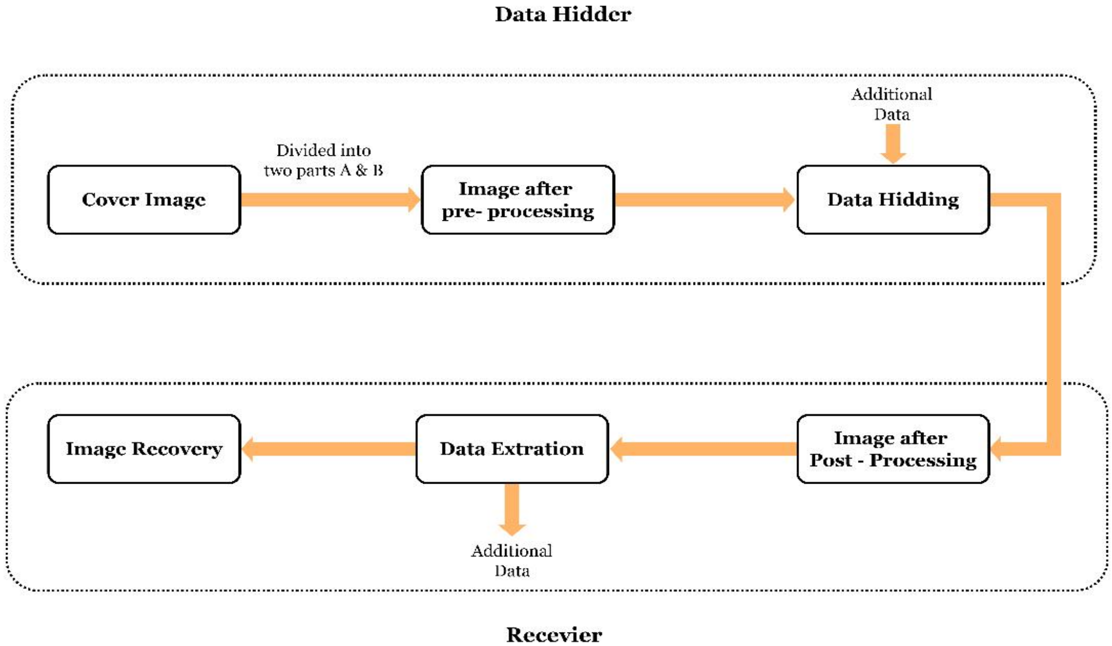


Figure 1 Flow diagram of the proposed RDH method

The pre-processing step is presented in Figure 2. The intensity ranges (will be covered later) are used to extract LSBs from A. These LSBs are gathered and joined into a bit stream. A conventional RDH approach is then used to reversibly embed the bit stream in part B. The LSBs that have been vacated in portion A contain additional data. Parts A and B are blended once more after data embedding to create a marked image with hidden data.

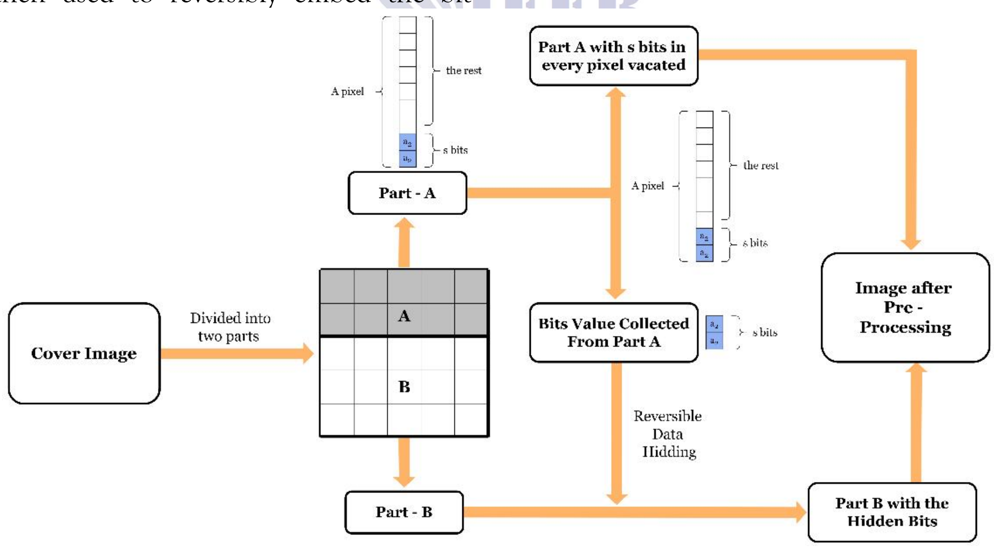


Figure 2 Data flow of the pre-processing step

Traditional RDH schemes treat all pixels equally—embedding the same number of bits regardless of image brightness. This results in high distortion in marked images. Data embedding based on pixel intensity is an area that need to exploited for RDH. We exploit a weakness in the HVS and Weber's law to define an RDH method. The HVS exhibits non-linear sensitivity to brightness i.e. data embedding in low intensity pixels results in small unnoticeable changes. Also, according to the Weber's law, modifications in high intensity pixels are tolerated without perceptible distortion.

Let the input image be represented as:

$$I = \{I(i,j) | 1 \leq i \leq M, 1 \leq j \leq N\} \quad (1)$$

where $M \times N$ is the spatial resolution of the image. The cover image I is divided into two parts A and B as

$$PartA = I(1{:}M/2, 1{:}N) \tag{2}$$

$$PartB = I(M/2+1{:}M, 1{:}N) \tag{3}$$

Since Part A will undergo intensity-based multi-bit replacement, the original LSBs of Part A must be preserved to guarantee full reversibility. These bits are extracted, organized into a serial bitstream, and later embedded losslessly into Part B. For each pixel $p \in Part\ A$, let the pixel intensity be represented in 8-bit binary as $p = b7 \quad b6 \quad b5 \quad b4 \quad b3 \quad b2 \quad b1 \quad b0$. Since the number of bits replaced depends on pixel intensity range (1 to 3 bits), the exact number of LSBs extracted from each pixel is determined during preprocessing.

Let $\boldsymbol{R(p)}$ denote the intensity range category of pixel $\boldsymbol{p}$:

$$R(p) = \begin{cases} 1, & p \in [0,31] \\ 2, & p \in [32,63] \\ 3, & p \in [64,127] \\ 4, & p \in [128,255] \end{cases} \tag{4}$$

The number of LSBs extracted equals the number of bits that will be replaced. All extracted LSBs are concatenated in raster-scan order to form the serialized LSB stream:

$$B = \bigcup_{p \in Part\ A} E_p \tag{5}$$

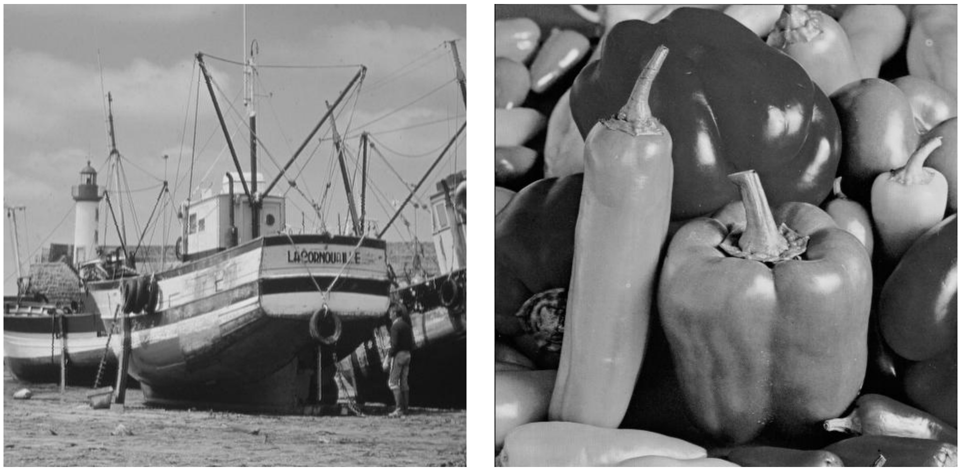
This serialized LSB stream B is embedded in Part B using the conventional histogram shifting based RDH method. First, a predictor is used to compute prediction errors. Then histogram of errors is built and identify peak bin P and zero bin Z. After this, bins are shifted between P and Z to embed bitstream S by modifying error values at peak bin. At the end pixel values are reconstructed to generate $I_B{}'$ which is the modified Part B of the cover image.

The LSBs of Part A are empty that are used to embed additional data reversibly. A simple LSB replacement method can be used to embed additional data to generate $I_A{}'$. Finally, both parts are combined to generate resultant marked image $I^{'}$ as

$$I^{'} = I_A^{'} \cup I_B^{'} \tag{6}$$

Experimental Results and Discussion

In this section, extensive experiments are conducted to evaluate the performance of the proposed intensity based RDH method. Implementation programs are developed using MATLAB 2018b under Windows 11 with Core i7 CPU and 8 GB RAM. Test images for experimental analysis are downloaded from the the CVG-UGR database (http://decsai.ugr.es/cvg/dbimagenes/). These are test images are illustrated in Figure 3 which are Boat, Pepper, Airplane, Baboon, Goldhill and Cameraman. The images covers a wide range of smooth and strongly textured, allowing for overall rating of perceptual embedding behavior across intensities.



(a) (b)

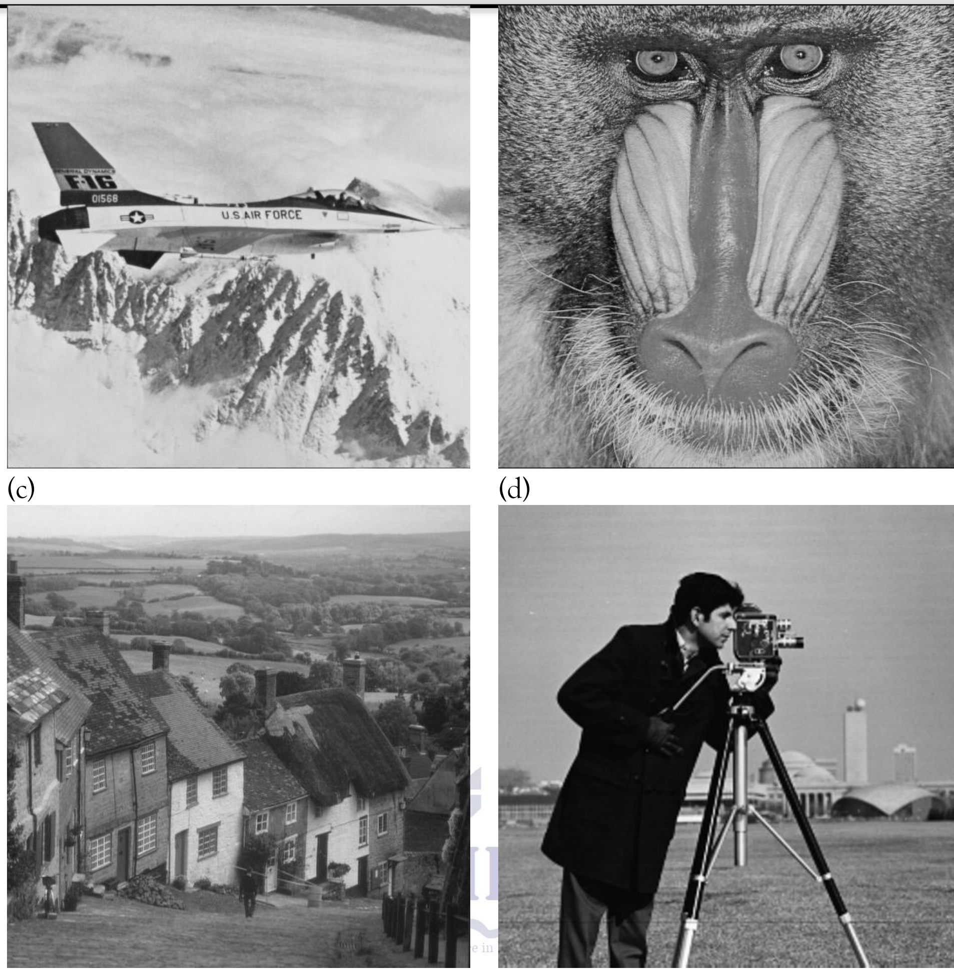

(c) (d)
(e) (f)

Figure 3 Test images: a) Boat, b) Pepper, c) Airplane, d) Baboon, e) Goldhill, f) Cameraman

4.1 Performance Evaluation

To analyze the performance of the proposed RDH method, we use embedding capacity (EC), embedding rate (bpp), Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). EC is the total number of bits embedded in the image. Embedding rate is the ratio EC to the size of the cover image. Embedding rate is measured in bits per pixel is calculated by Equation 7.

$$Embedding\ Rate = \frac{\text{Total embedded bits}}{(M \times N)} \quad (7)$$

PSNR measures perceptual fidelity of marked images and is computed by Equation 8.

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \quad (8)$$

Where 255 is the maximum pixel value and MSE is the mean square error.

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[x(i,j) - y(i,j)]^2 \quad (9)$$

Where $x(i,j)$ are the original pixel values and $y(i,j)$ are the distorted pixel values. Higher PSNR indicates better image quality.

SSIM evaluates image quality based on luminance, contrast, and structural consistency. SSIM is computed using Equation 10.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (10)$$

Where $\mu_x\mu_y$ are the mean intensity of images x and y, respectively, $\sigma_x\sigma_y$ are standard deviation of images x and y respectively, σ_{xy} is the Covariance between x and y , $C_1\,C_2$ are small constants to stabilize the division SSIM ranges between -1 and 1, where 1 indicates identical images. and 0 or less indicates no similarity. SSIM aligns better with human visual

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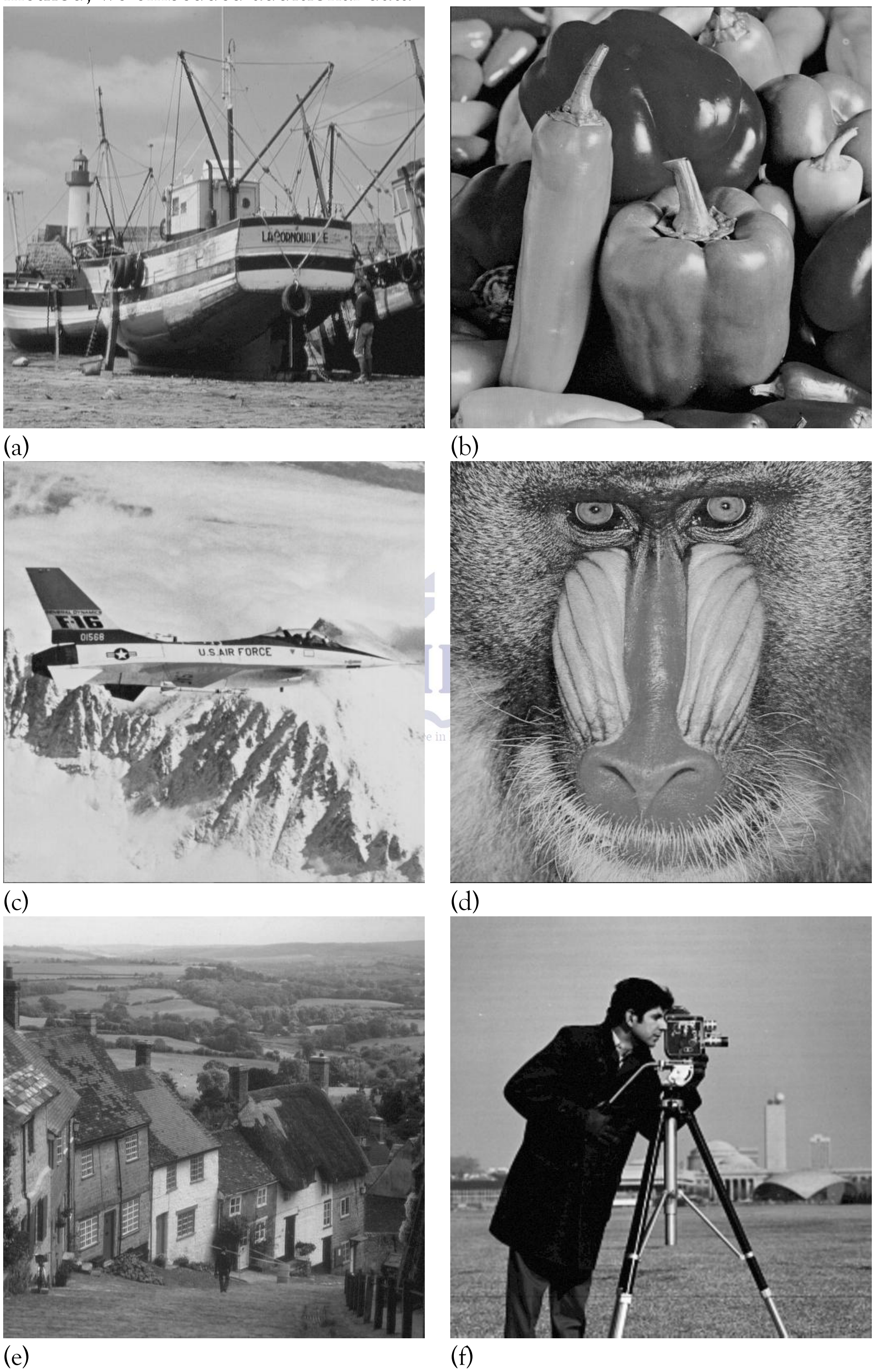
perception. It compares local regions to assess the overall structure.

To visually demonstrate the effectiveness of the proposed RDH method, we embedded additional data into test images to generate marked images as demonstrated in Figure 4.



(a) (b)
(c) (d)
(e) (f)

Figure 4 Visual quality of marked images

In order to illustrate how the PSNR changes with changing capacity, we recorded the PSNR at different embedding rates and then drew the rate distortion curve on them for the test there. The rate distortion curve shows in Figure 5 that PSNR slightly decreases with increasing embedding rate. Even for the largest embedding rate, PSNRs are still higher than 35 dB.

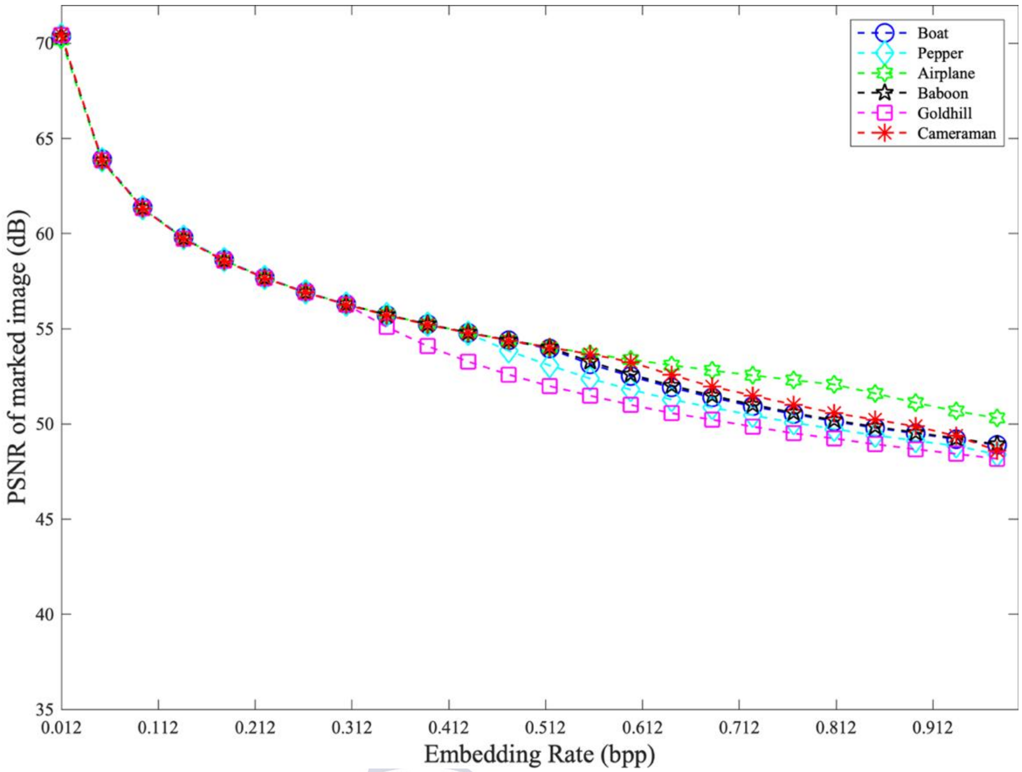


Figure 5 Rate distortion curves of test images

4.2 Comparison

The proposed method is compared with the HS by Ni et al., DE by Tian et al., PVO by Li et al., PPVO by Ou et al. and MHM by Wang et al. RDH methods. Table 1 lists ECs of different RDH methods compared to the proposed method for test images. The proposed method achieves higher EC than other methods especially 1.8–2 times higher capacity compared to PVO/PPVO. The increase is especially notable for smooth and mid-texture images. Even highly textured images (e.g., *Baboon*) show significantly improved capacity due to intensity-based multi-bit embedding.

Table 1: ***Embedding Capacity (bits ×10³) for Standard Images***

Image	HS (Ni et al.)	DE (Tian et al.)	PVO (Li et al.)	PPVO (Ou et al.)	MHM (Wang et al.)	Proposed
Boat	9.8	12.4	58.7	75.4	82.3	110.5
Pepper	7.4	11.3	51.1	72.8	79.2	104.6
Airplane	8.2	14.5	63.0	89.5	96.1	121.4
Baboon	10.1	13.2	57.4	78.6	86.9	118.2
Goldhill	6.4	10.8	22.5	35.3	40.1	64.7
Cameraman	8.1	12.9	54.9	74.2	82.7	114.1

Table 2 demonstrates the comparison of PSNR values between other RDH methods and the proposed method. Despite aggressive multi-bit embedding, the proposed method maintains PSNR above 40 dB for most images. HS methods have very high PSNR but extremely low capacity; thus the comparison is capacity-normalized. Proposed method outperforms DE, PPVO, and PVO in many cases at the same or higher embedding rate. For textured images (e.g., Baboon), the proposed PSNR is significantly better than PVO/PPVO.

Table 2: *PSNR (dB) of Marked Images*

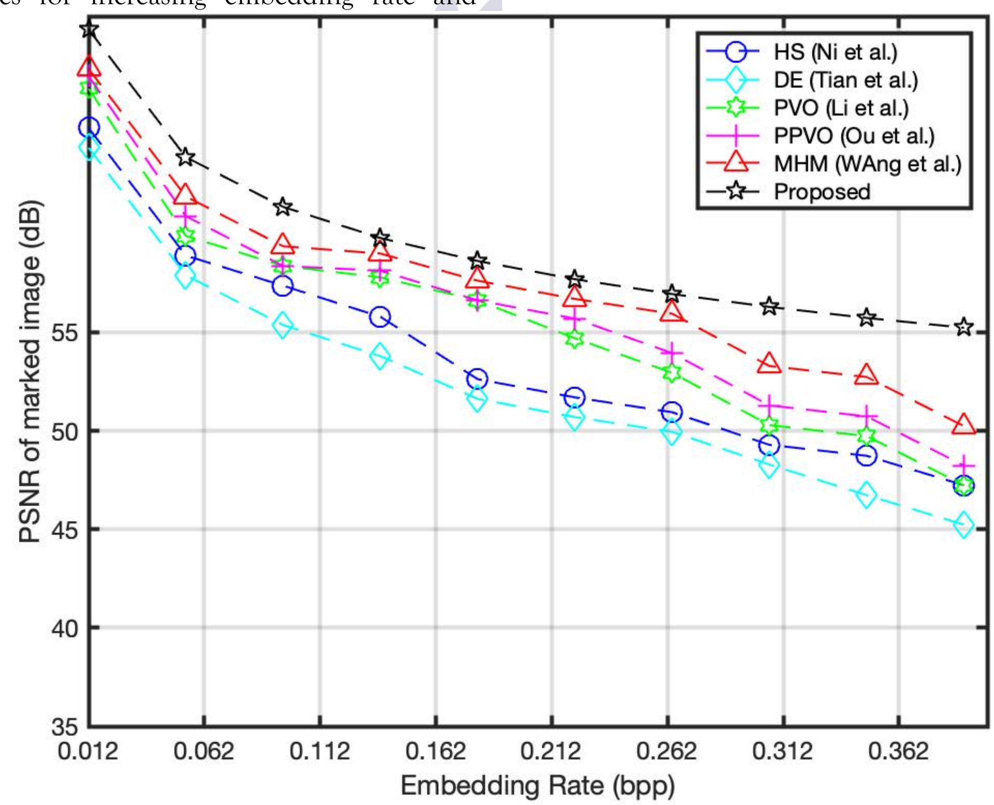
Image	HS	DE	PVO	PPVO	MHM	Proposed
Boat	48.2	45.1	48.3	49.0	50.8	**55.01**
Pepper	47.5	45.6	47.7	47.8	49.8	**55.24**
Airplane	44.5	43.6	45.7	46.7	47.7	**55.23**
Baboon	43.5	41.6	43.6	45.7	46.5	**55.85**
Goldhill	44.5	42.6	46.7	47.5	49.7	**54.08**
Cameraman	44.4	43.6	46.5	47.2	52.8	**55.21**

We also compare the embedding rate of the proposed method with the state-of-the-art methods as listed in Table 3. As seen, the proposed RDH method achieves embedding rate approaching 1 bit per pixel which is higher than all other methods.

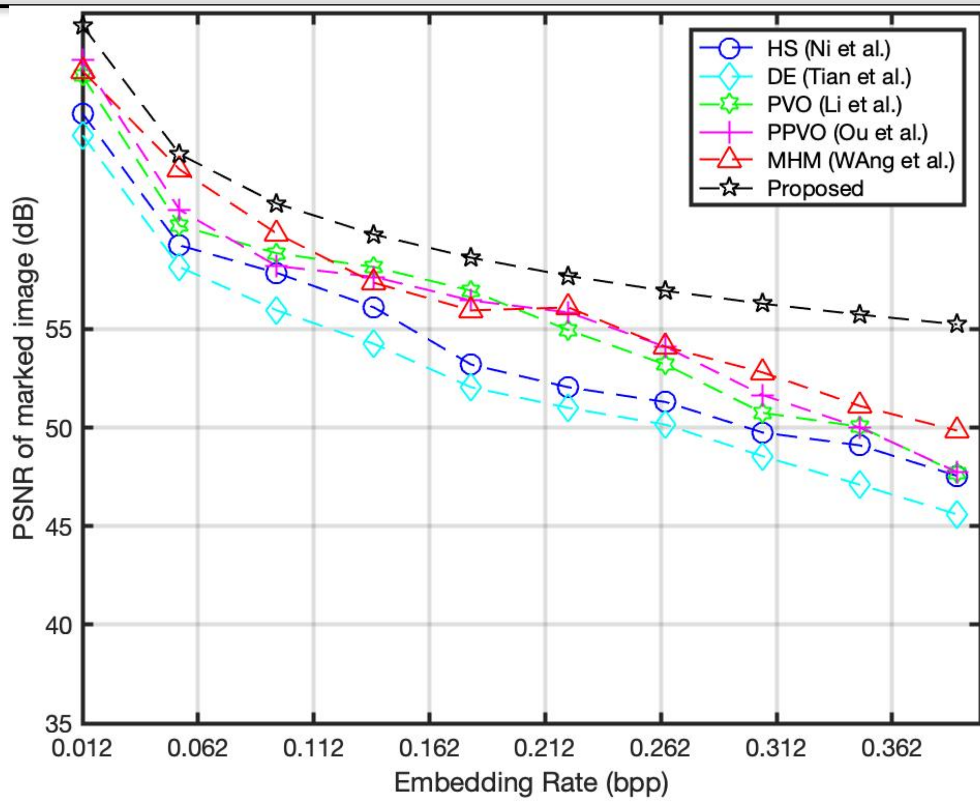
Table 3: *Embedding Rate Comparison (bpp)*

Method	Embedding Rate (bpp)
Ni et al. HS (2006)	0.9
Tian DE (2003)	0.4
Li PVO (2013)	0.7
Ou PPVO (2016)	0.7
Wang MHM (2020)	0.8
Proposed	1.0

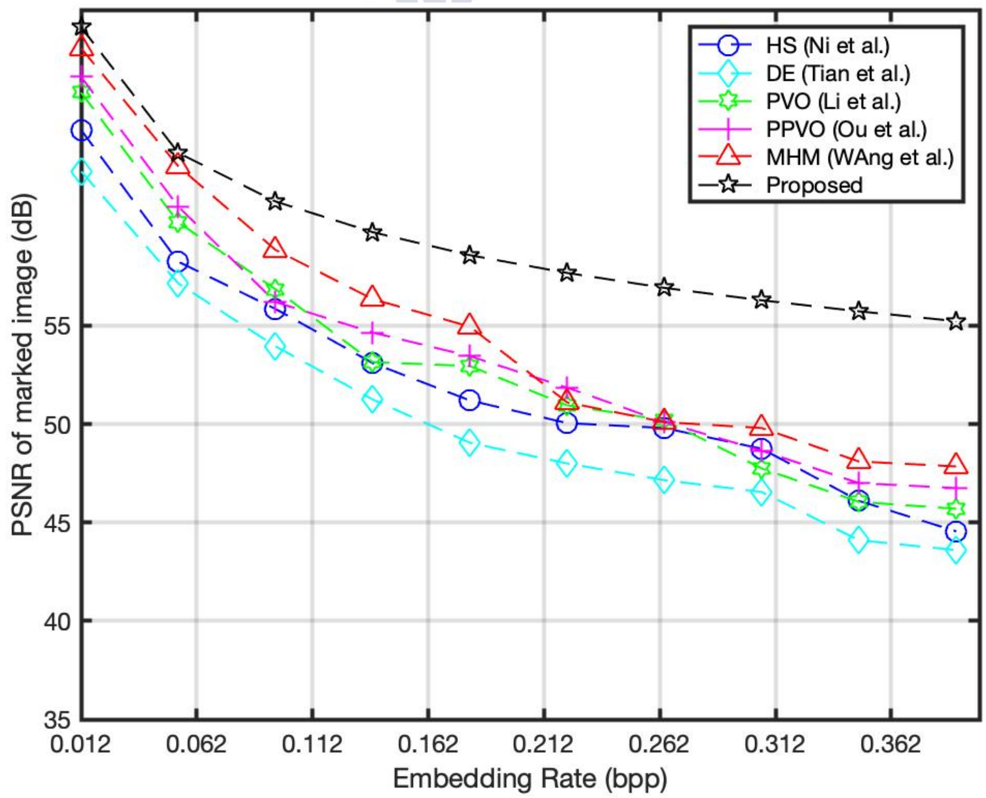
To further compare the proposed method with other state-of-the-art methods we computed PSNR values of all test images for increasing embedding rate and plotted the rate distortion curves as illustrated in Figure 6.



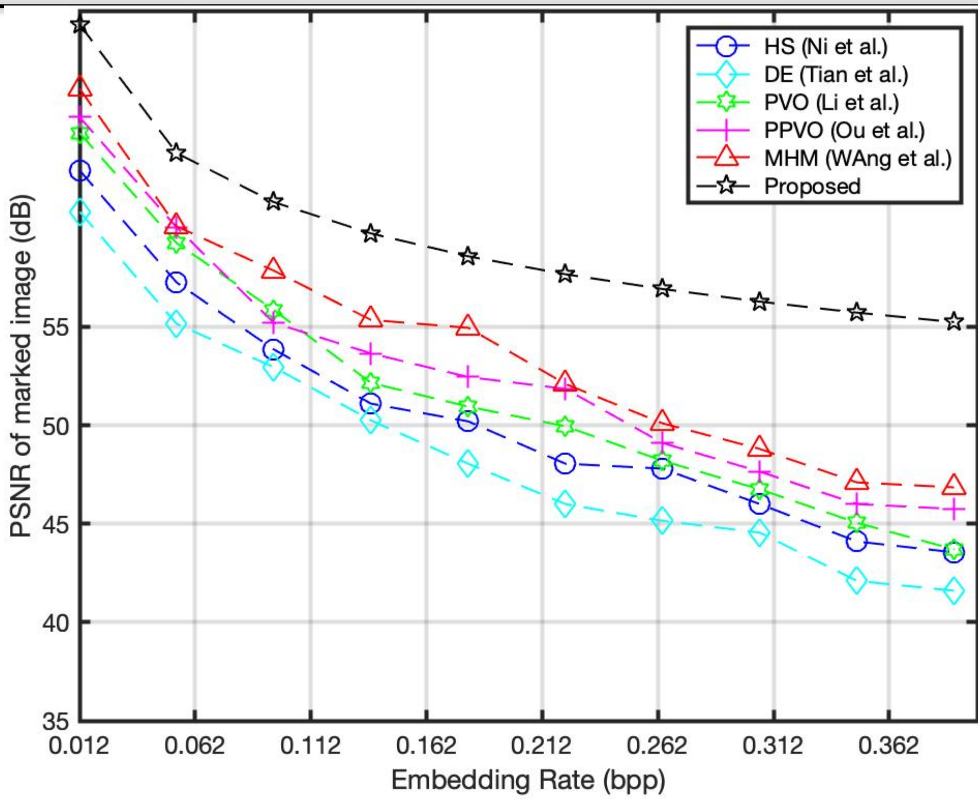
(a)


HS (Ni et al.)
DE (Tian et al.)
PVO (Li et al.)
PPVO (Ou et al.)
MHM (WAng et al.)
Proposed
PSNR of marked image (dB)
55
50
45
40
35
0.012
0.062
0.112
0.162
0.212
0.262
0.312
0.362
Embedding Rate (bpp)

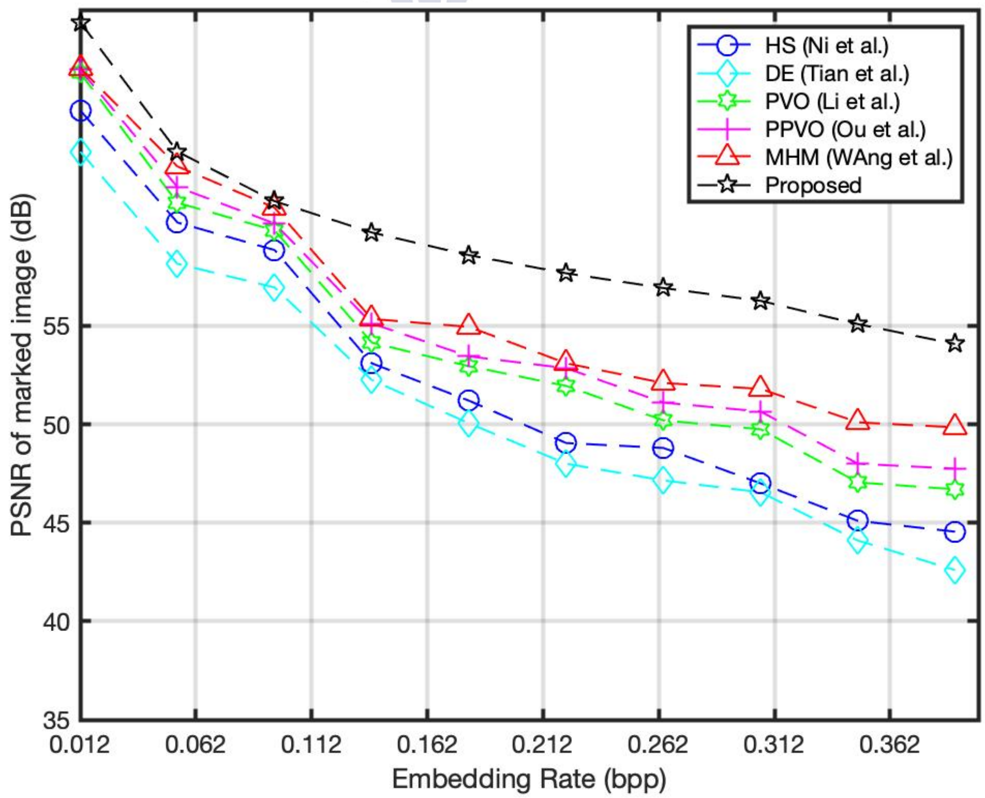
(b)


HS (Ni et al.)
DE (Tian et al.)
PVO (Li et al.)
PPVO (Ou et al.)
MHM (WAng et al.)
Proposed
PSNR of marked image (dB)
55
50
45
40
35
0.012
0.062
0.112
0.162
0.212
0.262
0.312
0.362
Embedding Rate (bpp)

(c)


HS (Ni et al.)
DE (Tian et al.)
PVO (Li et al.)
PPVO (Ou et al.)
MHM (WAng et al.)
Proposed
PSNR of marked image (dB)
55
50
45
40
35
0.012
0.062
0.112
0.162
0.212
0.262
0.312
0.362
Embedding Rate (bpp)

(d)


HS (Ni et al.)
DE (Tian et al.)
PVO (Li et al.)
PPVO (Ou et al.)
MHM (WAng et al.)
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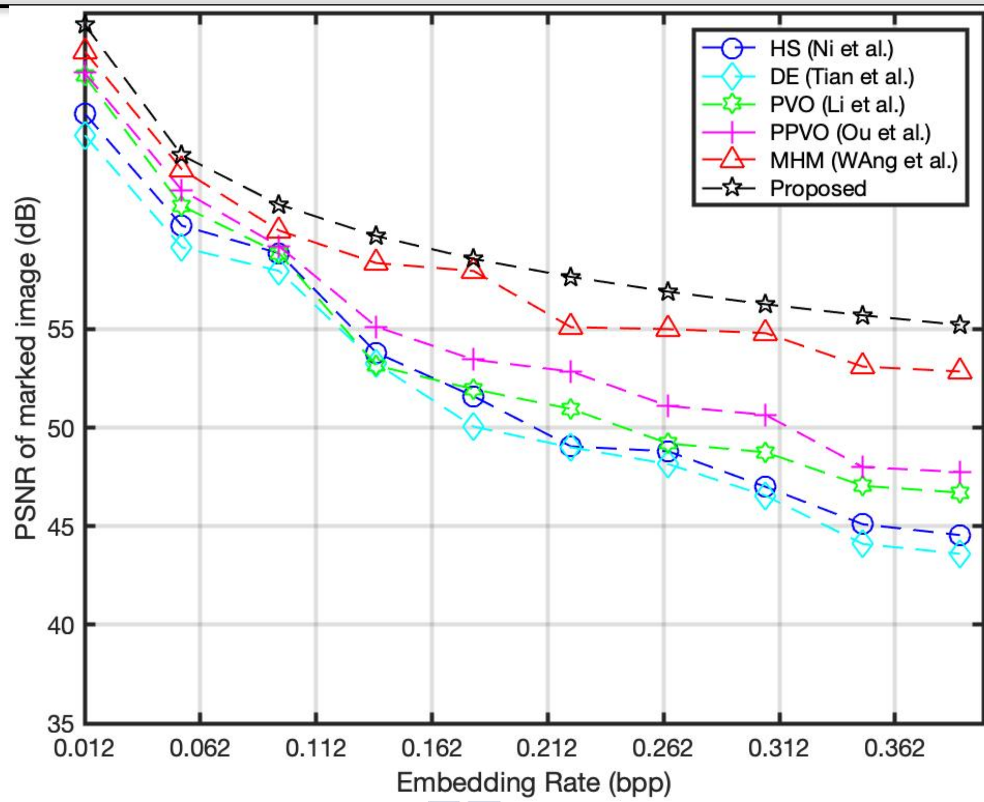
0.062
0.112
0.162
0.212
0.262
0.312
0.362
Embedding Rate (bpp)

(e)



(f)

Figure 6 Comparison of PSNR vs embedding rate between the proposed and five existing methods. a) Boat, b) Pepper, c) Airplane, d) Baboon, e) Goldhill, f) Cameraman

It worth noting that the PSNR values gradually decrease with increasing embedding rates for all RDH methods. For all test images, the proposed RDH method outperforms existing methods.

Conclusion

In this paper, an RDH method that embeds additional data based on pixel intensities is proposed. The data embedding procedure is motivated by HVS and Weber's law. The original cover image is divided into two parts. One part is used for additional data embedding and the other part is used for storing the LSBs of first part. As the proposed method allows for embedding 3 bits at maximum in cover image pixels, the achieved embedding rate depends on dynamic range of the image. The proposed embedding methods also results in high-quality marked images. The proposed RDH method is compared with existing state-of-the-art methods in terms of embedding capacity, embedding rate and PSNR. The proposed method outperformed all existing methods. In the future, we intend to extend the proposed method to color images. We shall explore color channel-specific embedding rule, managing perceptual sensitivity differences between color components and ensuring reversibility with multi-channel LSB storage.

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