Indian Journal of Science and Technology, *Vol 9(28), DOI: 10.17485/ijst/2016/v9i28/92733, July 2016*

ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Efficient Combinatorial Optimization Algorithm for Exploiting Modification Direction in Data Embedding

Ngoc Tu Huynh[1*], K. Bharanitharan[2] and Huan Sheng Hsueh[3]

[1]Faculty of Information Technology, Ton Duc Thang University, No.19 Nguyen Huu Tho Str., Ho Chi Minh city, Vietnam; huynhngoctu@tdt.edu.vn.

[2]Department of Electronic Engineering, Hanyang University, Seoul, South Korea; dharan@ieee.org

[3]Department of Computer Science and Information Engineering, National Chung Cheng University, Chiayi, Taiwan; a0919059585@gmail.com

Abstract

Background/Objectives: Steganographic techniques embed a secret to host cover to conceal its content. Among several methods for data embedding, Exploiting Modification Direction (EMD), which is simple and efficient, has attracted a lot of attention lately. **Methods/Statistical Analysis**: However, the recent schemes based on this method have high stego-image distortion. In this paper, we employ combinatorial optimization algorithm, also known as Hungarian algorithm to reorganize the secret sequences. **Findings**: As a result, we can remarkably reduce the distortion and achieve the best quality of stego-image. Moreover, experimental results show that our scheme is stable under different scenarios regardless of common case, worst case, or best case. **Application/Improvements**: Due to the simplicity and efficiency, the method is suitable for real-time application. This method is improved further to enhance embedding capacity while remaining the image quality.

Keywords: Data Hiding, EMD, Hungarian Algorithm, Information Security, Optimization, Steganography

1. Introduction

Distributing digital files such as images, videos, audios and other multimedia data safely over Internet has gained great deal of attention along the development of computer and communication technology. Among many security techniques, data hiding is a mechanism that embeds a secret into a host cover to obscure its content. The image containing embedded data is called stego-image, which is similar to the cover image but with small distortion. The major concern in data hiding is how to trade-off between the image quality and embedding capacity. Many steganographic methods have been proposed in the past few years. Basically, secret bits can be embedded into three kinds of domain: spatial domain[1–5], compressed domain and frequency domain[6]. In the spatial domain, pixels themselves can be modified to embed secret. Thus, high embedding capacity can be achieved. One of the simplest hiding techniques in spatial domain is the Least-Significant-Bit (LSB) substitution method proposed by Turner in 1989[1]. In this scheme, LSBs of the cover pixels are replaced to embed binary secrets[1–4]. The LSB method increases/decreases even/odd pixels by one, respectively, or keeps them unchanged. This asymmetric alteration causes the method vulnerable to common attacks. Later, Chan and Cheng[4] proposed a method called Optimal Pixel Adjustment Process (OPAP) to enhance the image quality by reducing the distortion cause by the LSB substitution. In 2006, Mielikainen proposed a method named the LSB matching revisited to improve the LSB substitution[2]. The LSB matching revisited scheme can resist steganographic attacks since four embedding rules combined with the binary

Author for correspondence

function are proposed to embed two secret bits into a cover pixel pair instead of using asymmetric modification. In this scheme, the first pixel is used to carry one secret bit while the binary function carries another bit. Therefore, Mielikainen's method achieves 1 Bit Per Pixel (bpp) of hiding capacity and good visual quality. Moreover, in the whole image, we have a ¾ chance of pixel value has to be modified by one and yet another ¼ chance of pixel value is kept unchanged. Hence, the MSE of the method is 0.375.

However, Mielikainen's scheme[3] does not explore all the modification direction. To fully exploit the modification directions of Mielikainen's scheme, Zhang and Wang[5] proposed the Exploiting Modification Direction scheme (EMD). In which the capacity of Zhang and Wang's method is $\log_2(2\times n + 1)/n$ bpp. When n equals 2, this method achieves its maximum embedding rate, which is approximate 1.16 bpp. Later on, Lee et al.[10] proposed an improved method to enhance the embedding capacity by segmenting the pairs of cover pixels. Thus, the payload of Lee et al.'s method is $\log_2(2n+1)/2$, which is higher than Zhang and Wang's. In 2009, Jung and Yoo[11] proposed an enhanced version of EMD method which increases the capacity significantly since in their scheme each cover pixel can carry one secret digit in a $(2n+1)$-ary notational system. Therefore, their capacity is two times higher than the original method. However, in Jung and Yoo's scheme, the image quality is decreased and lower than the original EMD method. In 2010, Wang et al.[12] also improved EMD method in terms of embedding efficiency and visual quality using section-wise strategy. Moreover, the method reduces the possibility of detection.

Hungarian algorithm solves matching problem or an assignment linear programming problem in general. This study uses the Hungarian method to solve matching problem occurred in EMD method. In this paper, we generalize EMD method and minimize pixel modification to achieve the optimal circumstance in which the stego-image has the best quality while maintaining the high embedding capacity. Our approach exploits Hungarian algorithm to determine which combination is optimal when a pixel pair is mapped to EMD table. Therefore, the number of modification of each pixel pair to embed a secret digit is reduced.

The rest of this paper is organized as follows. In Section 2, we briefly review the EMD method and Hungarian algorithm. The proposed scheme is described in Section 3. In Section 4, we demonstrate the experimental results of our scheme as well as compare the results with some previous ones. Finally, Section 5 is our conclusion.

2. Literature Review

2.1 Data Hiding based on Exploiting Modification Direction Method

In 2006, Zhang and Wang proposed[5] an idea to generate a matrix, called EMD matrix, which has a property that the relationship of any two pixels is limited to five directions: upward, downward, left, right or center. The method incorporates the LSB concept of modifying one LSB bit in selected pixel group to embed secret. Figure 1 shows an example of the EMD matrix when the group size is two.

The above details give brief descriptions and more details can be found at Zhang and Wang's scheme[5].

2.2. Hungarian Algorithm

2.2.1 The Mathematical Model

Let C be the cost matrix sized n × n of an assignment problem in which the ith resource is assigned to the jth task. C is defined as below.

$$C = \begin{bmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,n} \\ c_{2,1} & c_{2,2} & \cdots & c_{2,n} \\ \vdots & \vdots & \cdots & \vdots \\ c_{n,1} & c_{n,2} & \cdots & c_{n,n} \end{bmatrix}$$

In the cost matrix, each entry position represents an assignment and its cost is the sum of the n entries. An assignment is called an optimal assignment if the cost reaches the smallest possible cost.

2.2.2 The Hungarian Method

In order to find an optimal assignment, the Hungarian theorem, which is described as follows, is applied to a given $n \times n$ cost matrix.

	0	…	11	12	13	14	15	16	17	18	… p_{i+1}
0	0	…	2	4	1	3	0	2	4	1	…
:	:	:	:	:	:	:	:	:	:	:	
11	1	…	3	0	2	4	1	3	0	2	…
12	2	…	4	1	3	0	2	4	1	3	…
13	3	…	0	2	4	1	3	0	2	4	…
14	4	…	1	3	0	2	4	1	3	0	…
15	0	…	2	4	1	3	0	2	4	1	…
16	1	…	3	0	2	4	1	3	0	2	…
17	2	…	4	1	3	0	2	4	1	3	…
18	3	…	0	2	4	1	3	0	2	4	…
:	:	…	:	:	:	:	:	:	:	:	…
p_i											

Figure 1. EMD Matrix

Step 1. For each row: reduce each entry by the smallest value of the row.

Step 2. For each column: reduce each entry by the smallest value of the column.

Step 3. Cover all the zero entries of the matrix by drawing lines through appropriate rows and columns; then we will use the minimum number of such lines for the next step.

Step 4. Test for Optimality: An optimal assignment of zeros is possible *if and only if* the minimum number of covering lines equals to n. The algorithm is done here.

In case the minimum number of covering lines is less than n, proceed to Step 5.

Step 5. Find the smallest entry which is not covered by any line to subtract from each uncovered row, and then add it to each covered column. Return to Step 3.

2.3. Application of Hungarian Method to the Matching Problem in EMD Method

There are $(2n+1)$ different digit values a $(2n+1)$-ary notational system and $(2n+1)$ different values in EMD table, and each digit must be matched to a value in the EMD table. It is assumed that whenever we want to embed a secret digit into a pixel pair, we have to find a matching value on EMD table. Therefore, we create a matrix to record the number of times when a secret digit is matched to an EMD element. Then, operations of the Hungarian method are demonstrated as follows.

2.3.1. Appearance Matrix

A_{ij} denotes the appearance times, which a secret digit is changed to an EMD element.

$$A = \left[A_{ij}\right]_{(2n+1)(2n+1)} = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1,2n+1} \\ A_{21} & A_{22} & \cdots & A_{2,2n+1} \\ \vdots & \vdots & \vdots & \vdots \\ A_{2n+1,1} & A_{2n+1,2} & \cdots & A_{2n+1,2n+1} \end{bmatrix},$$

where i, j = 1, 2, …, $2n+1$.

3. Highest density matrix

$$R_i = \max\left(A_{i\_row}\right)$$

4. Proposed Scheme

In this section, the concept of Hungarian algorithm is exploited to achieve the optimal results for EMD embedding in gray scale images. First, secret message is converted to $(2n+1)$-based digits. Then, we generate the cost matrix of the value of secret digits and the elements of EMD table. The elements of this matrix are the number of times when the secret digits and the EMD elements are matched. Table 1 is an example used to illustrate the density of changing values.

4.1.1 Embedding Procedure

Our method first converts all pixels of a secret image into 2n+1-ary notational system to get secret digits. On the other hand, all the secret digits are from 0 to 2n, in which, n is the number of cover pixels which is used each time to embed a secret digit. The steps of our proposed scheme are described as follows.

Step 1. At the beginning, a binary secret sequence is translated into 2n+1-ary notational digits sequence. Therefore, the range of decimal digits is from 0 to 2n. For example, if n=2, the binary secret sequence will be converted into digits sequence in which each value is from 0 to 4.

Step 2. Pick a group of n pixels g_1, g_2,…,g_n from original image and use Eq. (1) to calculate f.

$$f(g_1, g_2, \ldots, g_n) = \left[\sum_{i=1}^{n}(g_i \times i)\right] \bmod (2n+1) \tag{1}$$

Step 3. Create a (2n+1) × (2n+1) table T to record a state in which the mapping value f needs to be shifted to embed the secret digits. The first column of this table is the value of f and first row contains the secret digits. For example, if a value of f is 4 and corresponding decimal secret is 3, the location of (3, 4) in table T will be increased by 1.

Step 4. Repeat Step 2 and 3 until all the digits are embedded.

Step 5. For each row of table T, we choose the max value and record relation of the corresponding f and

Table 1. Example to illustrate the density of changing values

Secret digits / EMD elements	0	1	2	3	4
0	3354	3335	3140	3363	3137
1	6667	6453	6557	6454	6546
2	6678	6470	6585	6610	6476
3	6441	6504	6605	6710	6627
4	3306	3189	3329	3307	3229

the secret digit. Next, set the maxima and all the values belong to its column and row be 0. Step 5 is repeated until we can find out all (2n+1) relations between f and secret digits.

Step 6. Using all (2n+1) relations, we can create a converting table and rearrange the original secret digit sequence. For example, if one of relationship is (2, 3) and all the digit 2 in original digit sequence will be rearranged to 3.

Step 7. Using EMD with new digit sequence, we can get the best quality of embedded image. The stego-image and the converting table will be sent to receiver to help him extract the embedded secret.

Let us give an example to demonstrate the Embedding procedure step by step.

Step 1: Create a table as shown in the Figure 2. The column represents secret data that will be embedded. The row is the corresponding value on EMD table.

The Figure 2 below illustrates the details of embedding procedure. In this figure, the array on left hand side shows the original pixel values. The right hand side table is an EMD table whose n equals to 2 in this example.

Now, the first pixel value pair (2, 3) in red rectangle is mapped to EMD table to get the corresponding value on EMD table that is 3. We want to embed the first secret digit "1". Thus, we add 1 at the position (3,1) in the table (the red "+1" in Figure).

Also, the next blue pixel pair (3,1) is mapped to EMD table to get the mapping value "0". This time we embed secret digit "0". Thus, we add "1" at position (0,0) (the blue "+1").

Similarly, the next pixel pair is (5, 4). The mapping value of this pixel pair on EMD table is "3" and we want to embed secret digit "2". We will plus "1" at (3, 2).

Finally, we can get the table as illustrated in Figure 3.

Step 2: We will find out the optimal combination in the table. There are two rules for choosing the best combination. First, at every row and column we can only pick up a value. Second, adding up all the

The secrets will be embedded

The corresponding value on EMD table

	0	1	2	3	4
0					
1			+1		
2					
3					
4					

Figure 2. Example for table *T* in n = 2.

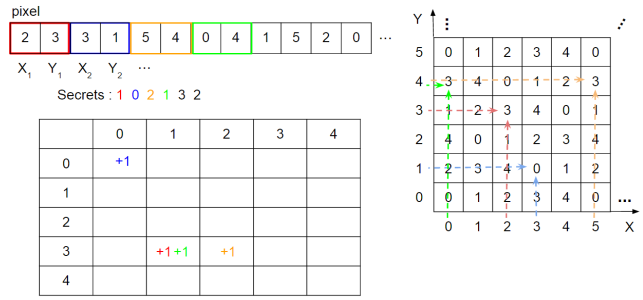

Figure 3. Example to illustrate embedding procedure.

	0	1	2	3	4
0	3273	3289	3216	3305	3216
1	6629	6609	6596	6448	6646
2	6471	6521	6504	6471	6672
3	6611	6653	6398	6638	6402
4	3449	3243	3302	3193	3317

Figure 4. Example for table *T* with number.

value we choose will yield the maximum value. To follow the rules, we use "Hungarian algorithm" to find out the best combination. In this example, we get the values 3305, 6596, 6672, 6653 and 3449 as shown in the Figure 4.

Step 3: When we get the maxima values 3305, 6596, 6672, 6653 and 3449, we create a table to change all the secret data that will be embedded. In the first matching value (0, 3) = "3305", all the digits "3" in secret data sequence will be changed to "0" and embedded. Similarly, (1, 2) = "6596" means the secret digit "2" will be modified to "1" and embedded.

Finally, we have this secret data conversion table and we rearrange all the secret sequence. For example, "0" is replaced by "4" and "1" is replaced by "3" and so on (Figure 5). The new secret data sequence is then embedded into cover image. And we will get best image quality in EMD scheme.

4.2 Extracting Procedure

When receiver wants to extract the secret data, he/she can perform the inverted steps of the embedding procedure, which are described as follows.

Step 1. Receiver generates the EMD table and uses it to extract data.

Step 2. Secret data can be extracted using the same process of the EMD method.

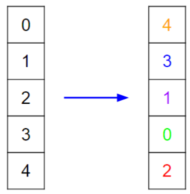

Figure 5. Data conversion table.

Step 3. After extracting secret digits, receiver remaps them into converting table to get the original secret digits sequences in (2n+1)-ary notational system.

Step 4. All the digits are converted into binary sequence to get the original secret data.

5. Experimental Results

In this paper, we propose an optimal method, which aims to achieve the highest image quality for the data hiding based on EMD scheme. This section demonstrates a set of experimental results that prove our scheme can successfully achieve the objective.

To evaluate the efficiency of our proposed scheme, we used the sets of test images, which includes eight 512×512 gray scale images: "Lena", "Peppers", "Baboon", "Tiffany", "Barbara", "Boat", "Airplane" and "Sailboat".

5.1 Evaluated Parameters

5.1.1 Mean Square Error (MSE)

MSE represents the error between the original cover image and the stego-image generated by embedding secret data.

$$MSE = \frac{1}{M \times N} \sum_{i=0}^{M} \sum_{j=0}^{N} \left(I_{ij} - I'_{ij}\right)^2 \tag{2}$$

where $M \times N$ denotes the size of images, I_{ij}, I'_{ij} denote the pixels values of the original image and the stego-image, respectively.

5.1.2 Peak-Signal-to-Noise Ratio (PSNR)

We exploit peak-signal-to-noise (PSNR) to measure the image quality generated by the scheme. The PSNR parameter is defined as below:

$$PSNR = 10\log_{10}\left(\frac{H \times W \times 255^2}{\sum_{i=1}^{H}\sum_{j=1}^{W}\left[\left(O_{i+m,j+n} - WI_{i+m,j+n}\right)\right]^2}\right) \tag{3}$$

where, $H \times W$ is the image size, $O_{i,j}$ and $WI_{i,j}$ are the pixels of an original image and its watermarked image, respectively.

5.1.3 Structure Similarity (SSIM)

Besides, to evaluate the visibility error between the original watermark image and the extracted one using properties of human visual system, we use Structure Similarity parameter (*SSIM*)[14], which is defined by Equation (10). According to Wang et al.[12], human visual perception is exceedingly sensitive for extracting structural information from a scene. Therefore, SSIM measurement is a task of three comparisons: luminance, contrast and structure.

To compare the luminance of each image, we first compute its mean intensity:

$$\mu_{wi} = \frac{1}{H \times W} \sum_{i=1}^{H \times W} wi_i \quad \mu_{ew} = \frac{1}{H \times W} \sum_{i=1}^{H \times W} ew_i \tag{4}$$

where, $H \times W$ is the size of watermark image, $wi_{m,n}$ and $ew_{m,n}$ are pixel value of watermarked image and extracted watermark, respectively. The luminance comparisons function $l(wi, ew)$ is a comparison of μ_{wi} and μ_{ew}:

$$l(wi, ew) = \frac{2\mu_{wi}\mu_{ew} + C_1}{\mu_{wi}^2 + \mu_{ew}^2 + C_1}, \tag{5}$$

where, $C_1 = (K_1, L)$, $L \in [0,255]$, a constant $K < 1$.

To estimate the contrast of the image, the standard deviation is adopted as Equation (6):

$$\sigma_{wi} = \sqrt{\left(\frac{1}{H \times W - 1}\right) \sum_{i=1}^{H \times W - 1} \left(wi_i - \mu_{wi}\right)^2} \tag{6}$$

The contrast comparisons $c(wi, ew)$ is the comparison of μ_{wi} and μ_{ew}:

$$c(wi, ew) = \frac{2\sigma_{wi}\sigma_{ew} + C_2}{\sigma_{wi}^2 + \sigma_{ew}^2 + C_2} \tag{7}$$

The structure comparison is computed by:

$$s(wi, ew) = \frac{\sigma_{wi,ew} + C_3}{\sigma_{wi}\sigma_{ew} + C_3} \tag{8}$$

The similar structure measurement is computed by combining to yield:

$$CSSIM(wi, ew) = \left[l(wi, ew)\right]^{\alpha} \cdot \left[c(wi, ew)\right]^{\beta} \cdot \left[s(wi, ew)\right]^{\gamma}. \tag{9}$$

Finally, we use the mean to evaluate the image quality (also called *SSIM* for short):

$$SSIM(wi, ew) = \frac{1}{H \times W} \sum_{j=1}^{M \times N} CSSIM(wi, ew) \tag{10}$$

5.2 Quality Analysis

5.2.1 MSE Comparisons

Image distortion occurs when we embed secret information into cover images since we have to modify pixel values. In this paper, we use Mean Square Error (MSE), which is defined in Equation (2), to evaluate image quality. It is obvious that a smaller MSE indicates the stego-image has a better quality. We analyze our algorithm in different scenarios: worst case, best case and common case. In the best-case scenario, our scheme achieves a very low error (MSE $\approx$ 0.39). Moreover, the MSE value of the common case scenario is slightly increased 0.01 compared to the best case. It is shown that our proposed scheme is stable and efficient. Table 2 shows the MSE values of different stego-image in three scenarios.

To further demonstrate that our scheme achieves a higher visual quality, we compare the MSE values of the proposed scheme with Least Significant Bit (LSB), Exploiting Modification Direction (EMD), Optimal Pixel Adjustment Process (OPAP)[4], Diamond Encoding (DE)[7] and Adaptive Pixel Pair Matching (APPM)[13] method. Table 3 shows the MSE comparisons among these schemes.

Table 2. MSE values of the proposed method under different scenarios

Image	Common case	Best case	Worst case
Lena	0.4003	0.3985	0.4008
Baboon	0.4009	0.3990	0.4013
Tiffany	0.3996	0.3986	0.4013
Boat	0.4002	0.3988	0.4013
Airplane	0.3994	0.3988	0.4013
Peppers	0.4004	0.3982	0.4011
Goldhill	0.4001	0.3990	0.4008
Barbara	0.4003	0.3990	0.4013

Table 3. MSE comparisons of the proposed scheme with previous schemes

Image	LSB	EMD	OPAP	DE	APPM	Proposed
Lena	1.909	0.4003	1.149	0.888	0.642	0.3985
Boat	1.965	0.4002	1.145	0.885	0.640	0.3988
Peppers	1.905	0.4004	1.138	0.886	0.646	0.3982
Elaine	1.917	0.3996	1.138	0.891	0.638	0.3986
Sailboat	1.904	0.2000	1.144	0.886	0.641	0.1988
House	1.921	0.4005	1.147	0.889	0.632	0.3951

5.2.2 PSNR Comparisons

In addition, we visibly illustrate the proposed scheme and evaluate the quality according to the peak-signal-noise-ratio parameter (PSNR) which is defined Equation (3). Figure 6 shows the stego-images and their corresponding PSNRs.

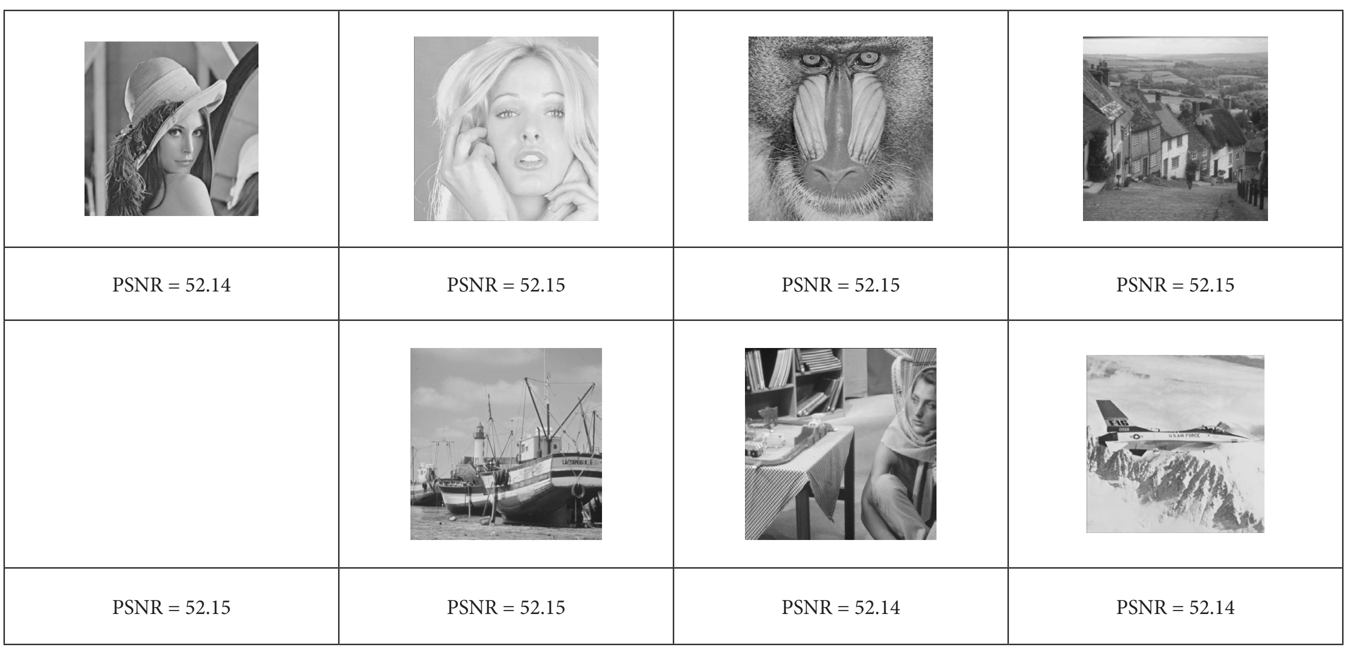

Figure 6. PSNR of stego-images.

Moreover, our method also performs well in different sizes of pixel groups (n). Figure 7 depicts the comparisons of PSNRs on several test images and the corresponding embedding rate when the group size is changed.

5.2.3 SSIM Comparisons

To illustrate the structure similarity (SSIM) of the proposed method, we implement our method on different test images. According to Table 4, comparing to the previous schemes, our scheme performs higher SSIM than that of others. Among these schemes, Wang et al.'s scheme[12] has the best performance in terms of visual quality. However, their SSIM values are lower than the results of our scheme. In general, our scheme achieves not only the better PSNR but also higher SSIM.

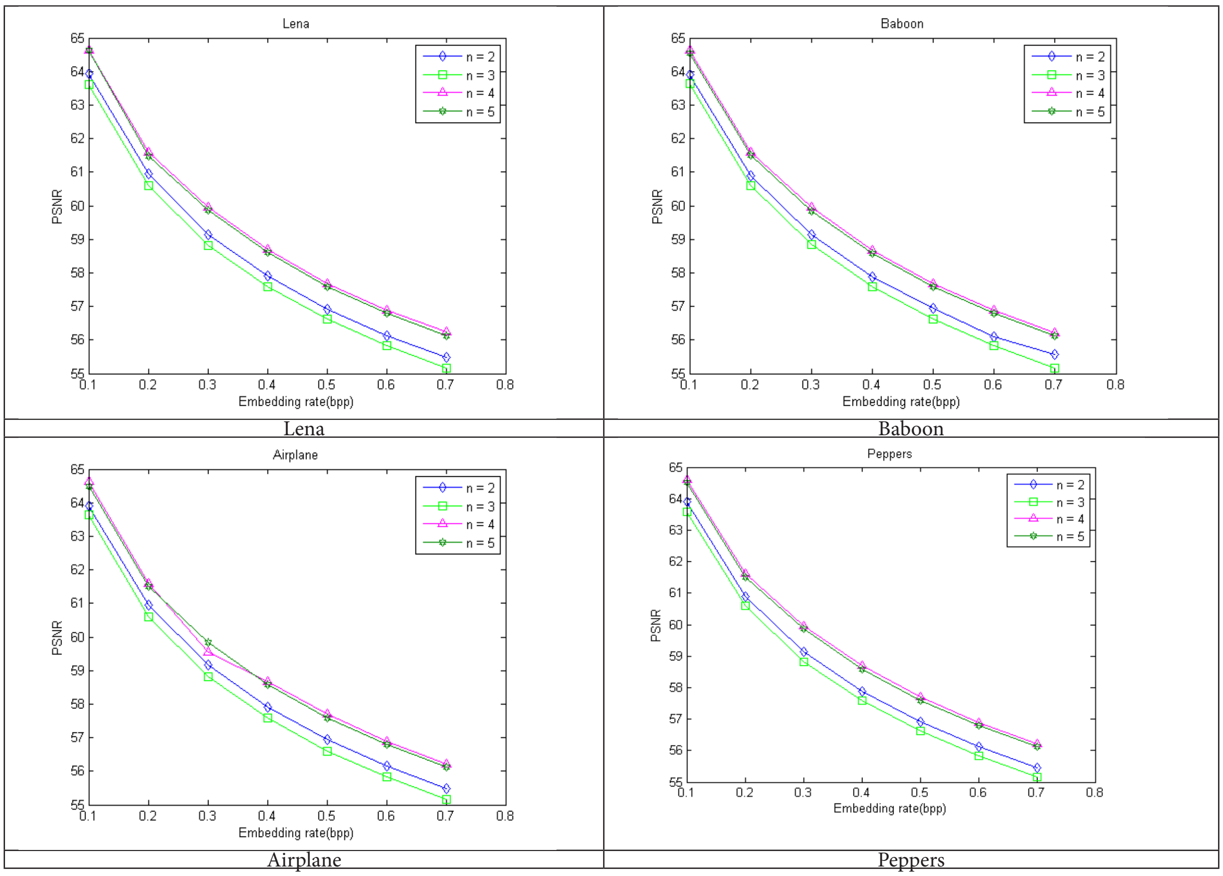

Figure 7. Comparisons of PSNR which different group size.

Table 4. Comparisons of PSNR and SSIM among the proposed scheme and previous schemes

	EMD		Jung and Yoo's method [10]		Chao et al.'s method [6]		Wang et al. [11]		Proposed method	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Lena	52.11	0.9971	48.13	0.9904	52.11	0.9970	52.92	0.9975	52.14	0.9991
Baboon	51.80	0.9989	48.12	0.9975	52.09	0.9988	52.93	0.9990	52.15	0.9997
Elaine	52.10	0.9978	48.12	0.9938	52.10	0.9976	52.92	0.9981	52.15	0.9988
Peppers	52.10	0.9972	48.15	0.9927	52.11	0.9970	52.93	0.9976	52.15	0.9992
Airplane	52.11	0.9967	48.13	0.9897	52.10	0.9964	52.93	0.9972	52.14	0.9987

6. Conclusions

In this paper, we propose an optimal solution for EMD embedding method to enhance the visual quality by reducing the distortion by modifying the cover pixels. In our scheme, the Hungarian algorithm is exploited to rearrange the original secret sequence. Therefore, the number of modifications on pixels is significantly reduced. The experimental results show that, with the same amount of embedded data, our scheme achieves better visual quality compared to that of some previous scheme.

7. References

1. Turner LF. Digital data security system. Patent IPN. 1989, WO 89/08915.
2. Dumitrescu S, Wu X, Wang Z. Detection of LSB steganography via sample pair analysis. IEEE Transactions on Signal Processing. 2003; 51(7):1995–2007.
3. Mielikainen J. LSB matching revisited IEEE Signal Processing Letters. 2006; 13(5):285–87.
4. Chan CK, Cheng LM. Hiding data in images by simple LSB substitution. Pattern Recognition. 2004; 37(3):469–74.
5. Zhang X, Wang S. Efficient Stegonographic embedding by exploiting modification direction. IEEE Communication Letters. 2006; 10 (11):1–3.
6. Thanikaiselvan V, Bansal T, Jain P, Shastri S. 9/7 IWT domain data hiding in image using adaptive and non adaptive methods. Indian Journal of Science and Technology. 2016; 9(5). DOI: 10.17485/ijst/2016/v9i5/87189.
7. Chao RM, Wu HC, Lee CC, Chu YP. A novel image data hiding scheme with diamond encoding. EURASIP Journal of Information Security. 2009 May 4.
8. Kuo WC, Chang SY. Hybrid GEMD data hiding. Journal of Information Hiding and Multimedia Signal Processing. 2013; 4 (2).
9. Kuo WC, Wang CC. Data hiding based on generalized exploiting modification direction method. The Imaging Science Journal. 2013; 61:484–90.
10. Lee CF, Chang CC, WangKH. An improvement of EMD embedding method for large payloads by pixel segmentation strategy. Image and Vision Computing. 2008; 26:1670–76.
11. Jung KH, Yoo KY. Improved exploiting modification direction method by modulus operation. International Journal of Signal Processing, Image Processing and Pattern. 2009; 2(1):79–87.
12. Wang J, Sun Y, Xu H, Chen K, Kim HJ, Joo SH. An improved section-wise exploiting modification direction method. Signal Processing. 2010; 90:2954–64.
13. Hong W, Chen TS. A novel data embedding method using adaptive pixel pair matching. IEEE Traction on Information Forensics and Security. 2012; 7(1).
14. Wang Z, Bovik AC, Sheikh HR, Simoncelli EP. Image quality assessment: from error visibility to structure similarity. IEEE Transaction on Image Processing. 2004; 13(4):600–12.