

Hiding Information in Image by Compound Meta-Heuristic Algorithm PSO-SA

Faramarz Sadeghi^{*1}, Marjan Kuchaki Rafsanjani², Fatemeh Zarisfi Kermani³

Department of Computer Science, Faculty of Mathematics and Computer
Shahid Bahonar University, Kerman-Iran

^{*1}farsad@uk.ac.ir ; ²kuchaki@uk.ac.ir ; ³fa_zarisfi@yahoo.com

Abstract- In this study a new method has been presented in order to hide secret information on host image, in a way that the image has been steganographed and has minimum difference to host image and is based on least significant bit (LSB). As security and quality are two main factors in evaluating steganography operation and LSB is a common method and is vulnerable against attacks and noises, researchers have set their priority on finding a substitution matrix in order to improve these two important factors and increase the system's efficiency. In this article, in order to find an optimal substitution matrix, a compound meta-heuristic method has been suggested which uses two optimization algorithms: Particle Swarm Optimization and simulated annealing. Results of simulation with two optimization algorithms PSO and SA and compound meta-heuristic algorithm PSO-SA have been comprised according to PSNR value and show that the stego-image produced by PSO-SA has more quality in comparison with other existing methods.

Keywords- *Steganography; LSB Substitution Matrix; Particle Swarm Optimization Algorithm; Simulated Annealing Algorithm*

I. INTRODUCTION

With the development of transmission technology and Internet appearance, wide possibilities have been provided in transmitting a great deal of data through networks. Since these networks increase the risk of illegal access, some methods, such as coding and hiding information, have been provided for the security of information and safe connection. Hiding information is a method to embed important and secret data into the typical digital media such as image, video, audio, text and multimedia as carriers which have been used widely in order to convey data through networks. Watermarking and steganography are two main branches of hiding information technology [1]. Image steganography [2, 3], where information is hiding within an image, has been used during the past decade.

On the image steganography, a digital image has been selected as a digital media cover to hide a secret message which is called cover image. This cover image involves a secret message embedded in it which is called stego-image. Steganography methods are categorized to spatial domain and frequency domain methods. Embedding in frequency domain methods like F5 [4], Model-based [5], Perturbed Quantization (PQ) [6], YASS [7], Contour-based steganography [8] and BSS [9] is done by modifications of suitably selected coefficients in a transform domain such as DFT¹, DWT², DCT³. The most common and simple spatial domains method is hiding information in LSB⁴ of cover image. Thus the secret message after it has been isolated to its producing bites and will be embedded to least significant bites of continuous pixels of cover image [3, 10]. Many LSB based data hiding techniques are proposed in recent years [10-17]. One of the disadvantages of LSB based method is the amount of differences between stego-image and cover image. As the possibilities of the explicit increase, two important factors i.e. security and the quality of stego-image would be in risk. In order to solve this problem and improve the quality of stego-image, a chaotic based approach has been proposed [13], besides using advantage of sharp areas in cover images for hiding data to improve the quality of stego-image and obtain high payload [14].

Another way which has been proposed to improve the performance of simple LSB method is the method of randomized process and optimal LSB substitution [15]. Farther, finding an optimal substitution matrix in this method, which can help decrease the differences and increase similarities with cover image, can be considered as an optimization problem. So far in order to obtain an optimal substitution matrix, a variety of optimization algorithms have been used [15, 16].

In this article, one compound meta-heuristic method, by using both SA⁵ and PSO⁶ algorithms, has been used to find optimal substitution matrix. So, first an optimal substitution matrix is found by use of PSO-SA algorithm and we encode secret image by using obtained matrix and finally embed the encoded secret image into cover image by replacing [15].

The rest of this paper is organized as follows: in Section 2, the conventional simple LSB substitution method and optimal LSB substitution method are reviewed. The compound meta-heuristic method (PSO-SA) is described in Section 3. The

¹ Discrete Fourier Transform

² Discrete Wavelet Transform

³ Discrete Cosine Transform

⁴ Least Significant Bit

⁵ Particle Swarm Optimization

⁶ Simulated Annealing

proposed steganography algorithm based on PSO-SA is discussed in Section 4 and the experimental results are given in Section 5. Finally, Section 6 summarizes the main conclusions and suggests the direction of future work.

II. CONVENTIONAL SIMPLE/OPTIMAL LSB SUBSTITUTION METHOD

Now, we describe two LSB substitution methods i.e. simple LSB substitution method [10] and optimal LSB substitution method [15] respectively:

A. Simple LSB Substitution

In Turner's method, first, the rightmost k LSBs from each pixel of n -bit gray-scale cover image X to form k -bit gray-scale image X' is retrieved. Second, the n -bit gray-scale secret image S by dividing each pixel into several k -bit units is converted to k -bit secret image S' so that each unit is treated as a single pixel. Finally, secret image can be embedded into cover image by replacing each pixel of X' with each pixel of S' .

B. Optimal LSB Substitution Method

However, the Turner's method with high capacity is simple but there exit some problems like high difference between the original cover image and the cover image after embedding (i.e. the low quality of stego-image), especially when k is larger than 3. So to solve this problem, an optimal LSB substitution matrix is proposed that is described as follows:

First we will decompose n bite security messages into several smaller k -bit units. Then we will calculate decimal value of k -bit security message in range of 0 to 2^k-1 and produce substitution matrix M as follows:

$$m_{ij} = \begin{cases} 1 & \text{gray value is replaced by gray value} \\ 0 & \text{do nothing} \end{cases} \quad (1)$$

It should be noticed that in each row and column of matrix M , one element is one and the other elements are zero. With this operation and replacement of security bites, a meaningless message will be produced which cannot recover the original message just by possessing transposed substitution matrix M . For example, with assumption $n=8$ bite for message A , we divided it into four 2-bit units and by using substitution matrix M , we will attain to encode A' . The substitution order is illustrated in Fig. 1.

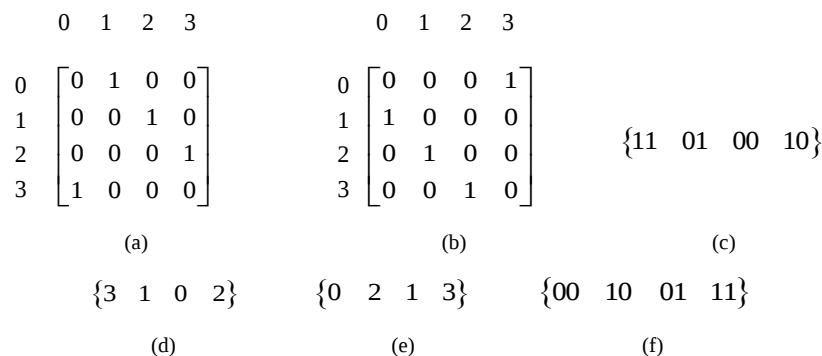


Fig. 1 An example of how to implement OLSB method for $k=2$. (a) substitution matrix M . (b) transpose matrix of M . (c) 8-bit secret message A . (d) decimal value of (c). (e) Substitution result of (d). (f) Binary value of (e) or the encrypted secret message

It is obvious that the total number of possible substitutions for k -bit images (i.e. $2^k!$) can be presented by $M_1, M_2, \dots, M_{(2^k)!}$. So, we have different substitution matrixes so that each of them will produce different encoding messages and eventually produce stego-image with different qualities which are calculated by PSNR value. In order to find optimal stego-image (i.e. the stego-image with the maximum PSNR value) through producing stego-images according to each substitution matrix, the different optimizing algorithms have been used, because if k becomes large, the number of possible substitutions will grow exponentially. Therefore, the proposed method by Ran-Zan Wang [15] has used the Genetic Algorithm and the proposed method by Zhi-Hui Wang [16] has used the Cat Swarm Optimization algorithm for finding the optimal substitution matrix that produces optimal stego-image.

III. COMPOUND META-HEURISTIC PSO/SA ALGORITHM

In this section we will design a compound meta-heuristic method for finding optimal substitution matrix. This method has used two PSO and SA algorithms to find optimal substitution matrix. In the first phase, because of improved structure of PSO algorithm, it constructs a set of answers, which are closer to global optimizing solution than the answers which are produced randomly. In second phase, the best answer of the previous phase is used as start state in SA algorithm.

A. Standard PSO Algorithm

PSO algorithm is an evolutionary computational model based on collective intelligence [18]. In order to consider search space, this algorithm will use a population of potential answers. Each individual of population has a velocity which moves according to it in search space and also has a memory which records best position that meets in search space up to now. So each individual tries to move to its own best personal position that he or she has visited so far, called $pbest_i$, and also the swarm's best position is called as $gbest$. In PSO algorithm, population is called as swarm and each individual is called as a particle.

PSO algorithm will start with an initial swarm of particles. Position and velocity of each i^{th} particle in D-dimensional problem space are $X_i = (x_{i0}, x_{i1}, \dots, x_{i(D-1)})$ and $V_i = (v_{i0}, v_{i1}, \dots, v_{i(D-1)})$, respectively. In each phase of executing of algorithm, performance of each particle is evaluated by a fitness function and each particle's velocity and position are updated according to the following equations:

$$v_i^{t+1} = w * v_i^t + c_1 * rand_1 * (pbest - x_i^t) + c_2 * rand_2 * (gbest - x_i^t) \quad (3)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (4)$$

$$w = w_{max} - t * \frac{w_{max} - w_{min}}{t_{max}} \quad (5)$$

whereas $pbest$ is the best position of a particle and $gbest$ is the best position of the particle swarm and $rand_1$ and $rand_2$ are two random variables with uniform distribution in $[0, 1]$ and c_1, c_2 are constant accelerations and w is the inertia weight, linearly decreasing from maximum value (called w_{max}) to a minimum value (called w_{min}) during executing of the algorithm [18], t is the current iteration number and t_{max} is the given maximum of iteration number. In addition, in order to control velocity, a limit has been used, so that velocity of each particle in each iteration of executing algorithm should be in $[-v_{max}, v_{max}]$. If the number of iterations exceeds t_{max} then executing of the algorithm will be stopped.

B. Standard SA Algorithm

This algorithm is an iterated improved solution and will simulate annealing process, in which a material is heated to a temperature more than its melting point and then its temperature reduces gradually. Reduction procedure is so slow that material would be on thermo dynamical balance. In other words, temperature of the material would be reduced in the way that best crystal structure will be produced with least energy in that temperature [19]. In this algorithm, suggested answers are on high temperature and are not suitable answers. So, algorithm tries to get access to better answer in low temperature through reducing temperature variable during executing time. This algorithm starts with a suggested answer and current temperature and then the next answer is produced with attention to current answer and according to the following procedure:

If we named current answer S and the new answer with name of S' would be produced in its neighbourhood. Amount of fitness function will be calculated for two answers and their differences would be calculated according to:

$$\Delta = f(s') - f(s) \quad (6)$$

According to [10] whereas $\Delta > 0$ then S' is accepted, otherwise this answer would be accepted with possibilities of $e^{-\Delta/T}$ in which T is controlling parameter of the temperature. It is observed that with decreasing the amount of T , resulted possibility by above equation is decreased and then unsuitable answer will be removed from searching system gradually.

Selecting initial temperature is important. This temperature should be large enough to make it possible to evaluate almost all the answers of the problem, but not so large that increases the solving time with unessential searching. Defining a neighbourhood depends on structure of the considered problem. With more gradient of the neighbourhood, algorithm is able to search more parts of solution space. In order to reduce temperature several methods have also been considered among which the most used one is geometry method which will be mentioned later:

$$T_{t+1} = \lambda^t * T_0 \quad (7)$$

Whereas t is the current iteration number, T is initial temperature and λ is rate of temperature reduction and is a number lower than 1 and closer to 1, it shows that the time duration of the algorithm is longer, but quality of the final answer would be better. The condition of stopping this algorithm is accessing to a special temperature, usually 0, or accessing to maximum of the executing iterations of the algorithm.

IV. THE PROPOSED METHOD

As is mentioned in introduction, in this paper, for hiding secret information in an image, a compound meta-heuristic

algorithm resulted by PSO and SA algorithms has been presented.

A. Structure of the Proposed Method

The whole proposed procedure can be divided into 4 phases:

Phase 1: Finding optimal substitution matrix M by using compound meta-heuristic PSO-SA algorithm.

Phase 2: Encoding secrete image.

Phase 3: Embedded encoding image of second phase in a cover image by using substitution matrix M .

Phase 4: Sending stego-image along with substitution matrix M .

1) Finding Optimal Substitution Matrix by Using Compound Meta-Heuristic PSO-SA Algorithm:

In applied PSO algorithm, each particle p with $2k$ dimension will be defined as $p=p_0p_1\dots p_{2k-1}$ in which p_0 is 1 position on 0th row of the substitution matrix, p_1 is 1 position in first row etc. A substitution matrix M and matched particle P is shown as a sample in Fig. 3.

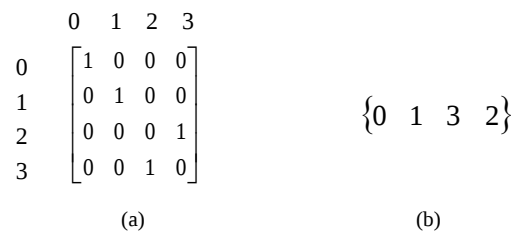


Fig. 3 (a) The substitution matrix M and (b) corresponding particle p for $k=2$

It is obvious that each particle is matched with a substitution matrix. Therefore, each particle with best value of fitness function is equal to substitution matrix which can produce stego-image. Each particle P should be a vector of integer numbers in range of 0 to 2^k-1 . But with applying Equations (3) and (4) in each iteration of executing of algorithm, a vector with non-integer values for any particle will be produced. In order to solve this problem, we have used a mapping in which a non-integer value in vector p will be mapped to an integer value. Thus a maximum non-integer value which exists in vector P to 2^k-1 , maximum non-integer value between reminded values of vector P to 2^k-2 etc will be mapped. A vector P with non-integer values and a vector resulted by mapping with integer values have been presented in Fig. 4.

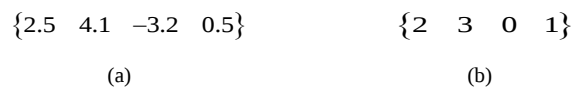


Fig. 4 (a) Vector P with non-integer values (b) mapped vector

Usually in most image processing problems, PSNR⁷ and MSE⁸ are parameters for measuring the quality of the picture. In this study PSNR value is used as a fitness function. PSNR value of a gray-level image can be calculated as follows:

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

$$MSE = \frac{1}{W*H} \sum_{i=1}^W \sum_{j=1}^H (S_{ij} - C_{ij})^2 \quad (9)$$

in which S_{ij} and C_{ij} are intensity of ij pixel of the stego-image and the cover image, W and H are the pixel numbers for the width and the height of the cover image respectively.

Initial answer of SA algorithm is equal to best resulted answer of PSO algorithm. Since vector which has been resulted as a neighbour answer and should be evaluated by fitness function has the same problem as the particles in PSO, which means that its value is a non-integer number, so mapping function which has been applied in PSO for particles has been used in the same manner as the answer vector of the neighbour in each iteration of the executing of SA algorithm. Besides fitness function for SA algorithm is the same fitness function in PSO algorithm.

According to what has been said up to now; the process of producing substitution matrix M is as below:

Phase 1: initial swarm is made of K particles, with position X_i and velocity V_i , that have been generated randomly. For each particle $pbest_i = X_i$, and so PSNR of each particle will be calculated and the particle with the largest PSNR is set as a $gbest$.

⁷ peak signal to noise rate

⁸ mean square error

For each particle in the swarm, following phases have been done:

Phase 2: velocity and position of each particle have been updated by using Equations (3)-(5).

Phase 3: mapped result of the new position for each particle should be calculated and then its corresponding PSNR should also be calculated. If it is larger than $pbest_i$ then $pbest_i$ is updated with a new position X_i . If it was also larger than $gbest$ then $gbest$ will be updated with a new position X_i , otherwise $pbest_i$ and $gbest$ will not be changed.

Phase 4: If t , number of iteration, is lower than t_max we go to *phase2*. Otherwise the algorithm should be stopped and the $gbest$ is selected and we will continue in *phase 5*.

Phase 5: the selected $gbest$ from *phase 4* will be as initial answer S and also as the best found solution ($bestsol$) for SA algorithm, also an initial value will be selected for T .

Phase 6: a neighbour answer S' will be generated and its Δ and PSNR values will be calculated. If $\Delta > 0$ then S' will be selected as current answer and if PSNR is larger than $bestsol$ then $bestsol$ will be updated with S' , otherwise we will move to *phase 7*.

Phase 7: A random number with uniform distribution between $[0, 1]$ is produced and placed in r and if $r < e^{-\Delta/T}$ then S' would be assumed as current answer.

Phase 8: new temperature will be calculated and placed on T .

Phase 9: if $T \neq 0$ or iteration number t is lower than t_max we will back to *phase 6*, otherwise algorithm will be stopped and $bestsol$ would be returned.

TABLE 1 PARAMETERS SETTING FOR PSO ALGORITHM

Parameter	Value
acceleration constant	2
$[W_{min}, W_{max}]$	$[0.4, 0.9]$
$[V_{min}, V_{max}]$	$[-4, 4]$
Iteration number	4
Dimension	$2^k!$ ($k=2$ or $k=4$)

TABLE 2 PARAMETERS SETTING FOR SA ALGORITHM

Parameter	Value
Initial temperature	100
rate of temperature reduction	0.95
gradient of the neighbourhood (d)	1.6
Iteration number	25
Dimension	$2^k!$ ($k=2$ or $k=4$)

2) Image Encoding by Using Substitution Matrix:

After calculating optimal substitution matrix M , we will encode a secrete image according to the procedure which was mentioned in Section II-B.

3) Embedding of Encoding Image by Using Matrix M :

Images which are used in this paper are 8-bit gray level images with gray levels from 0 to 256. In order to embed the secret image in cover image, we execute the proposed algorithm as follows:

Step 1: Convert the n -bit gray-scale cover image X and secret image S to k -bit gray-scale images X' and S' , respectively.

Step 2: Execute the described PSO-SA algorithm in phase 1 to find the optimal or near optimal substitution matrix M .

Step 3: Encode the secret image S' according to matrix M by using phase 2 to obtain the encoded secret image S'' .

Step 4: Replace cover image X' with encoded secret image S'' to obtain the stego-image Y .

Step 5: Save Y into an image file and the obtained optimal or near-optimal substitution matrix M in a text file as KEY.

4) Sending Stego-image Along with Substitution Matrix M :

Send image file Y and text file KEY, which are obtained from previous phase, into receiver.

B. Extracting Process

Secrete image can be extracted through the following phases from stego-image:

Step 1: Extract the right most k LSBs of each pixel in the stego-image Y .

Step 2: Decode the extracted bits according to KEY.

Step 3: Compose the decoded bits and obtain the pixels of original secret image.

V. IMPLEMENTATION

In our experiment, we implement three methods by using MATLAB software to find optimal or near-optimal substitution matrix. These methods are optimal LSB substitutions using Particle Swarm Optimization, optimal LSB substitution using Simulated Annealing Algorithm and our proposed method (i.e. optimal LSB substitution using compound meta-heuristic PSO-SA algorithm). In our experimental test, all images are 256 gray levels shown in Fig. 5. We execute these methods for $k=2$ and $k=4$. For PSO and SA algorithms, we set the parameters shown in Tables 1, 2, respectively.

In this section, we compared the results of our implementations with three methods of LSB substitution i.e. simple LSB substitution, optimal LSB substitution using Genetic Algorithm and optimal LSB substitution using Cat Swarm Optimization strategy.

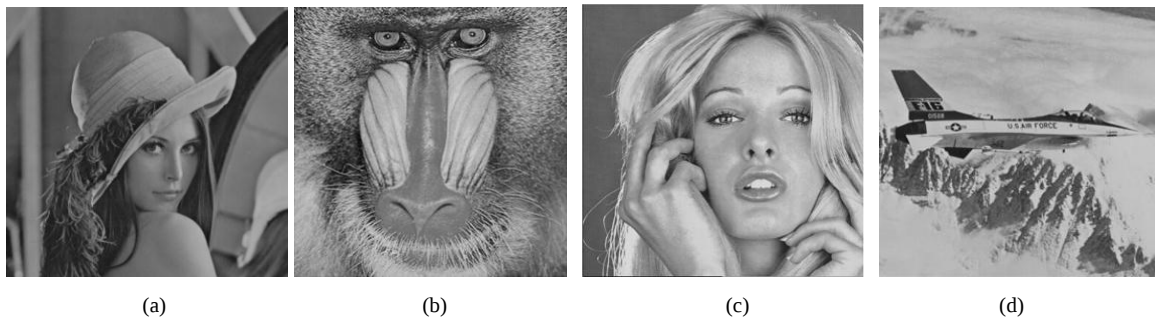


Fig. 5 The images in our experiments. (a) Lena, (b) Baboon are cover images and (c) Tiff, (d) Jet are secret images.

As we know, the visual quality of stego-image and embedding capacity of cover image are two important criteria in evaluating a steganography method. Because the embedding capacity of these methods is the same, so our experiments of comparison focus on visual quality of setgo image. Thus, in order to validate the performance of the implemented methods in this paper and other three methods of LSB substitution, we used two images, Lena and Baboon of 512*512 sizes for cover images and two images, Jet and Tiff of 256*256 size (first class) and 256*512 size (second class) for secret images. Finally, we analyse the stego-image quality between implemented methods and other three methods based on PSNR value.

The results of implementation in first class are shown in Table 3 and Figs. 6, 7.

TABLE 3 THE PSNR VALUES BETWEEN COVER IMAGES AND STEGO-IMAGS ($K=2$)

cover	method	Jet	Tiff
Lena	Simple LSB substitution	43.96	43.96
	OLSB substitution using GA [15]	44.53	44.9
	OLSB substitution using CSO [16]	44.63	44.53
	The proposed PSO approach	44.59	44.55
	The proposed SA approach	43.96	43.54
	The proposed PSO-SA approach	47.56	47.24
Baboon	Simple LSB substitution	43.96	43.96
	OLSB substitution using GA [15]	44.54	44.9
	OLSB substitution using CSO [16]	44.64	44.52
	The proposed PSO approach	45.14	44.19
	The proposed SA approach	43.35	44.37
	The proposed PSO-SA approach	47.35	47.20

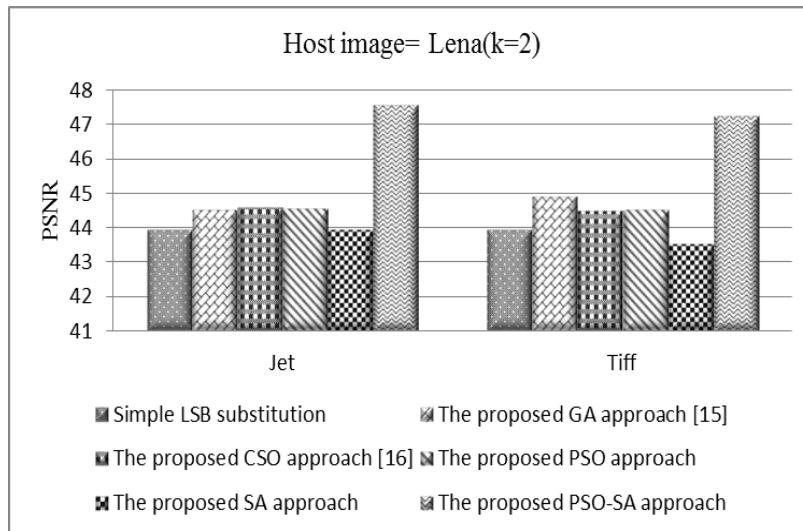


Fig. 6 The results of embedding secret images in Fig. 5 into Lena as cover image

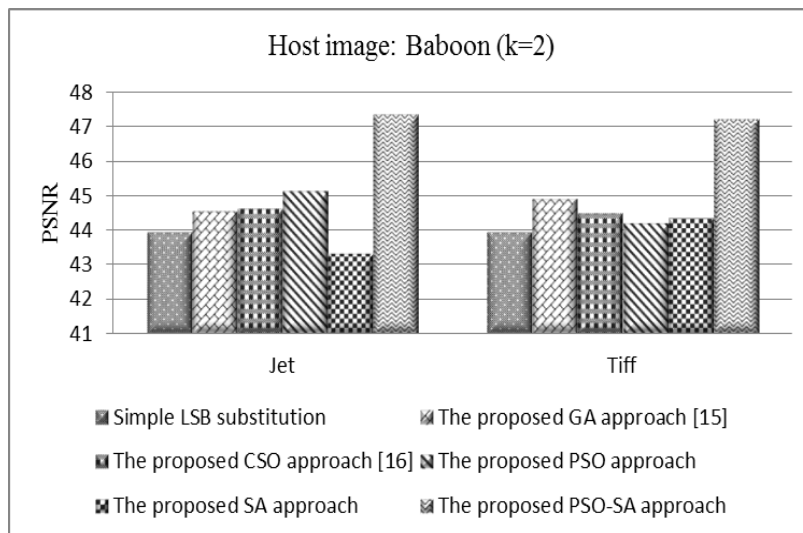


Fig. 7 The results of embedding secret images in Fig. 5 into Baboon as cover image

In Table 3, we can find the PSNR values of five first methods for embedding the secret images into 2 rightmost least significant bits of the cover image that are almost the same, but the PSNR value of the proposed method i.e. the optimal LSB substitution using compound meta-heuristic PSO-SA algorithm is always higher than the other methods between 2 dB to 4 dB. This value is different for each cover image and given secret image.

Also, the results of implementation in second class are shown in Table 4 and Figs. 8, 9.

TABLE 4 THE PSNR VALUES BETWEEN COVER IMAGES AND STEGO-IMAGS (K=4)

cover	method	Jet	Tiff
Lena	Simple LSB substitution	32.04	31.21
	OLSB substitution using GA [15]	32.71	32.90
	OLSB substitution using CSO [16]	32.86	32.81
	The proposed PSO approach	35.58	35.61
	The proposed SA approach	35.13	34.92
	The proposed PSO-SA approach	35.52	35.25
Baboon	Simple LSB substitution	32.11	31.31
	OLSB substitution using GA [15]	32.79	32.95
	OLSB substitution using CSO [16]	32.90	32.87
	The proposed PSO approach	35.30	35.24
	The proposed SA approach	34.97	35.30
	The proposed PSO-SA approach	35.29	35.84

From the exhibited results in Table 4, we can see that the PSNR values of these three methods (i.e. the proposed PSO approach, the proposed SA approach and the proposed compound PSO-SA approach) are always higher than other existing methods between 2 dB to 4 dB.

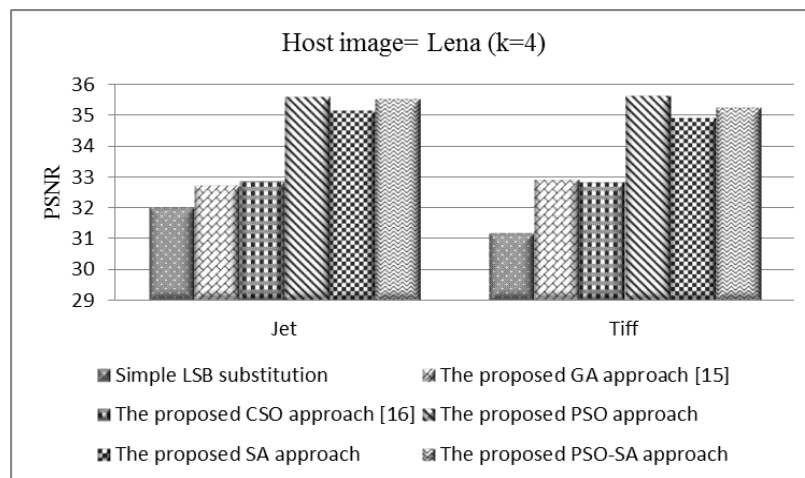


Fig. 8 The results of embedding secret images in Fig. 5 into Lena as cover image

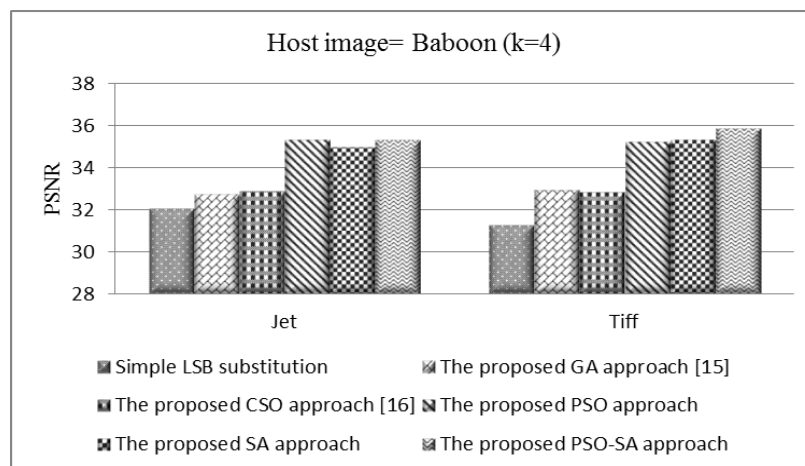


Fig. 9 The results of embedding secret images in Fig. 5 into Lena as cover image

Finally, according to the experimental results presented through tables and figures, we can observe that the produced stego-images by each optimal LSB substitution method has almost better visual quality than the produced stego-image by simple LSB substitution. Now we see that the obtained result by employing the compound meta-heuristic PSO-SA algorithm has better performance. So the proposed compound optimization algorithm yields the optimal or near-optimal solutions.

VI. CONCLUSIONS AND FUTURE WORK

Steganography has been used in order to keep safe the secret information during transmission through different connection channels by Internet. Since security and quality are two main factors in evaluating steganography operation and common LSB method is so vulnerable against attacks and noise, in order to improve these two important factors and increase system's efficiency, researchers have set their priority on finding a substitution matrix. In this way in order to find an optimal substitution matrix, in this paper a compound meta-heuristic method has been suggested. This compound algorithm will start with optimizing PSO algorithm and will continue with SA algorithm. According to PSNR value, the comparison of results of performing compound meta-heuristic PSO-SA algorithm, with two optimization algorithms SA and PSO, shows that a stego-image resulted by suggested PSO-SA algorithm has more quality in comparison with other existing methods. In addition, the suggested method has high level of security since no one can extract and encode secret image without having substitution matrix. In the future, we are going to employ the other optimization algorithms like imperialist competition algorithm (ICA) for optimizing parameters of hiding image and text instead of considered algorithms.

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