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On the Efficiency of Metaheuristic Optimization for Adaptive Image Steganography in the DFT Domain

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***Abstract*—Adaptive embedding is a popular area of image steganography. Adaptability means the use of cover image features in the embedding process. In many cases, the embedding adaptability is associated with choosing the best position of the message bits in the image. However, the total check of all possible options for the message fragment is redundant in most cases. This leads us to the optimization problem. In this paper, we investigate the applicability of some classical metaheuristic optimization algorithms for solving the problem of increasing the efficiency of adaptive embedding of information into the discrete Fourier transform phase spectrum. We consider three popular optimization algorithms: the genetic algorithm, the differential evolution algorithm, and the particle swarm optimization algorithm. The experimental results show that the particle swarm optimization algorithm can significantly increase the embedding capacity, while the imperceptibility also improves or remains at the same level, and the embedded information is extracted without any errors.**

***Index Terms*—steganography, genetic algorithm, differential evolution, particle swarm optimization, discrete Fourier transform**

I. Introduction

Information security is an important aspect of creating a comfortable and secure digital space. Digital steganography is a promising technology for protecting information during transmission over communication networks. Steganography techniques allow us to hide secret messages in media objects such as digital images. The transmission of stego image does not attract attention because secret message is invisible for third parties. Therefore, it is possible to successfully create covert data transmission channels using image steganography.

Balancing various embedding performance metrics such as capacity, imperceptibility, and bit error rate is challenging. Adaptive steganography algorithms ensure flexible adjustment of the algorithm characteristics for each specific cover image. They have high levels of embedding quality [1], [2], [3]. A popular trend of the adaptive steganography algorithms development is the selection of the best positions for hiding message bits. Obviously, we can find the best option and reach the highest embedding efficiency by searching through all possible options. However, the total check of all possible options for the message fragment location in the image data elements is redundant in most cases. Usually, to ensure a high level of security, it is enough to find not the best embedding options, but close to them. To do this, we can use various optimization methods.

In this paper, we investigate the effectiveness of using some metaheuristic optimization algorithms to find the best embedding option for adaptive information embedding in the phase spectrum of the Discrete Fourier Transform (DFT).

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II. Related work

Authors of many studies use metaheuristic optimization methods to improve the efficiency of steganographic algorithms. Genetic Algorithm (GA) is the most common solution. For example, in [4], GA is used to find the best sequence of operations during the execution of a steganographic algorithm, such as pixel scanning, pixel shifting, flipping secret bits, and others. This scheme ensures the optimal arrangement of secret message bits in the cover image. The authors of study [5] use GA-based optimization when embedding information in the Discrete Cosine Transform (DCT) domain of digital images using the Least Significant Bit (LSB) method. GA increases the robustness of the algorithm and allows it to withstand against any rigorous testing and brutal attack. In [6], a modified version of GA is used to find the optimal coefficients of Fresnelet transform or Discrete Ripplet transform for data hiding. In [7], a scheme for secure transmission of medical data based on a bit mask oriented GA is proposed that combines steganography and encryption.

Particle Swarm Optimization (PSO) algorithm is another popular optimization algorithm. In [8], PSO is used to find the best pixel locations in a cover image to embed a secret message. The authors compare the effectiveness of 3 different PSO versions: Standard PSO, Quantum Behaved PSO, and Human behavior - Based PSO. In [9], PSO is used to improve the quality of Pixel-Value Differencing method. The optimization algorithm chooses the ideal pixel gray values among numerous modulus function solutions. The authors of [10] use PSO to provide high embedding capacity in the spatial domain of images. Study [11] presents a steganographic method that hides information in Integer Wavelet Transform coefficients. The authors apply PSO to find the optimal substitution matrix for converting secret data into their substituted forms. In paper

[12], the authors propose a steganography scheme for the secure transmission of user's secret passwords. The scheme combines GA and PSO while embedding information in the coefficients of the bi-orthogonal wavelet transform. PSO is used to get an enhanced version of the cover image. GA chooses the best version of the hidden image.

Some authors use other metaheuristic optimization techniques. For example, in [13] the Ant Colony Optimization algorithm is used to detect a complex region of cover image when embedding information into a spatial domain using LSB method. Study [14] presents an algorithm of Artificial Bee Colony to optimize the block assignment for a secret image embedding. The authors demonstrate that their algorithm is better at resisting some noise attacks than similar steganographic schemes. Study [15] propose to use Differential Evolution (DE) to find the threshold values of the algorithm that provide the best ratio of the visual quality of stego image and capacity. The authors of [16] use Fruit Fly Optimization to find optimal locations for hiding data in a spatial domain. The information is embedded in the DCT coefficients of the most suitable pixels. The study [17] presents a steganographic algorithm based on the Fractional Fourier Transform. The task of finding the best pixel positions for embedding is solved using the Firefly Algorithm, and information embedding is performed using Histogram Shifting technique.

III. Adaptive embedding of information into the DFT phase spectrum

In this study, we evaluate the applicability of some optimization algorithms to improve the quality of adaptive information embedding in the DFT phase spectrum using the example of the embedding algorithm proposed earlier by the authors of this paper in [18]. We briefly describe this algorithm below.

The embedding procedure is applied to blocks of 8 × 8 pixels. The result of applying the DFT to the matrix of image pixels is a matrix of complex numbers (DFT coefficients) of the same size. The phase values of the coefficients are changed during embedding procedure. Not all coefficients are used for embedding, but only 21 elements of the embedding area. The phase values of the DFT coefficients are values from the range $(-\pi; \pi]$. Before embedding, it is necessary to select two values ϕ_0 and ϕ_1 from this range, such that $\phi_0 = -\phi_1$. Embedding of each bit of a secret message b into a phase value ϕ occurs according to the formula

$$\phi' = \begin{cases} \phi_0, & \text{if } b = 0; \\ \phi_1, & \text{if } b = 1, \end{cases} \tag{1}$$

where ϕ' is a phase value of the DFT coefficient after embedding.

A feature of the algorithm [18] is an iterative embedding procedure aimed at combating extraction errors caused by rounding. Iterative information embedding is as follows. After embedding a secret message fragment into the block of DFT coefficients phase values, information is extracted and extraction errors is checked. At the data extraction stage, inverse DFT is performed, the values are rounded to obtain integer pixels, and direct DFT is performed. The phase values can be distorted after all these operations, so we use the extraction interval, the width of which is determined by the parameter ε. The extraction formula is

$$b = \begin{cases} 0, & \text{if } \phi'' \in (\phi_0 - \varepsilon; \phi_0 + \varepsilon); \\ 1, & \text{if } \phi'' \in (\phi_1 - \varepsilon; \phi_1 + \varepsilon), \end{cases} \tag{2}$$

where ϕ'' is a phase value of the DFT coefficient at the extraction stage.

If errors are detected, the message bits are embedded into the "problem" coefficients again. This process continues until an option is obtained that provides error-free information extraction. If this cannot be achieved in a given number of iterations, then the block becomes empty. In this case, all phase values from the embedding area are changed so that they do not fall into the extraction intervals (2).

It is impossible to ensure error-free extraction of message bits from all coefficients of the embedding area without significantly degrading the quality of the stego image. This requires a very large number of iterations, and they distort the phase spectrum. Therefore, it is necessary to use the maximum number of elements of the embedding area, which simultaneously preserves the acceptable quality of the final stego image and achieves error-free extraction. This leads us to the problem of multi-criteria optimization.

IV. Optimization details

In this section, we discuss the optimization problem and present an objective function. In addition, we briefly describe the considered optimization algorithms and the features of their application in our subject area.

In Section 3, we have noted that 21 elements of the embedding area can be used to hide the secret message bits. However, to successfully process a block, it is necessary to achieve error-free extraction of all embedded bits or to make the block empty. For some blocks, a very large number of iterations are required to ensure error-free extraction, as a result distortions of the stego image become noticeable to the naked eye. The small number of iterations makes the embedding capacity extremely low, since most of the blocks are empty.

In [18], the amount of information embedded in each block varies for each block, depending on the characteristics of this block. In particular, it proposes to use for embedding only those phase values that fall into the extraction intervals (2) before embedding. Additionally, some values are used that do not fall into the extraction intervals; they are selected by checking possible options.

In this paper, we propose to consider each element of the embedding area as a possible object for change. This means that any element of the embedding area can either contain an embedded message bit or not, regardless of its original value. We call the specific list of changes made to the current block an embedding option. To find the best embedding option, we propose using metaheuristic optimization algorithms. In our study, we investigate the applicability of GA, DE, and PSO algorithms to this problem.

A. Genetic Algorithm

GA simulates the process of natural selection. At the first stage, the initial population is randomly generated. Individuals of the population are embedding options. In this case, the embedding option is a binary sequence, where one means that the phase value contains a bit of information, and zero means that the phase value does not contain a bit of information. At the second stage, a secret message fragment is embedded in accordance with each embedding option and the objective function values are calculated. Next, a new generation is formed by applying crossover and mutation operations with probabilities p_{cross}^{GA} and p_{mut}^{GA} respectively. Crossover is the creation of new individuals by combining part of the chromosomes of two different individuals of the current population. The mutation changes a randomly selected gene of the individual after crossover. After embedding and calculating the objective function values, the selection of surviving individuals with the best objective function values is performed. The process is repeated until the condition for stopping the algorithm is reached. In our study, such a condition is the achievement of a given number of generations.

B. Differential Evolution

The basic idea of DE is similar. However, in contrast to GA, DE works with real numbers, so the individuals of the population are vectors of real numbers. These numbers directly replace the phase values of the DFT coefficients at the first iteration of the embedding procedure. In this case, the embedding option not only shows whether the phase value contains a secret message bit, but also how the phase value changes. At the first stage, the initial population is generated. During the execution of the algorithm, each individual v is mutated according to the formula

$$v = v_1 + \alpha(v_2 - v_3), \tag{3}$$

where v_1, v_2, v_3 are randomly selected individuals, α is an algorithm parameter.

After that, the crossover operation is applied to each mutant vector with a probability p_{cross}^{DE}. New individuals are used to embed information, after which the objective function is calculated. If the new individual provides a higher objective function value, it replaces the previous one. After the end of the specified number of generations, the individual with the highest objective function value is selected.

C. Particle Swarm Optimization

The PSO algorithm was inspired by the behavior of flocks of birds in nature. This algorithm also works with real numbers, therefore, at the first iteration of the embedding procedure, the original phase values of the DFT coefficients are directly replaced by the found values. Unlike GA and DE, at the initial stage it is necessary to generate not the population of individuals itself, but their position and speed vectors. At each iteration, the best known position of each particle separately and the best known position of the entire swarm of particles are determined. They are used to calculate new values for the particle speed. The particle speed v changes according to the formula

$$v_{i+1} = wv_i + \psi_p r_p(x_p - x_i) + \psi_g r_g(x_g - x_i), \tag{4}$$

where r_p, r_g are random numbers, w, ψ_p, ψ_g are algorithm parameters, x_p is the best known position of the particle, x_g is the best position of the entire swarm of particles.

The particle position x changes according to the formula

$$x_{i+1} = x_i + v_{i+1}. \tag{5}$$

As a result, the best swarm state becomes a solution to the optimization problem.

D. Objective function

The main characteristics of the steganographic embedding quality are capacity and invisibility. Since the purpose of steganography is to hide the presence of additional data in a digital object, it is necessary to ensure high invisibility of embedding. A high capacity is also required for efficient information transmission over a covert channel. The achievement both of these indicators is an important task, therefore we use them when building an objective function.

Capacity is the number of bits of embedded information. Since the search for the best embedding option is performed for each individual image block, for the objective function we use the capacity of the current block $C_{block} \geq 1$. The maximum value of the block capacity C_{max} is 21 bits. For the convenience of using the capacity component in the objective function, it should be in the range $(0; 1]$. Thus, the capacity component is expressed by the formula

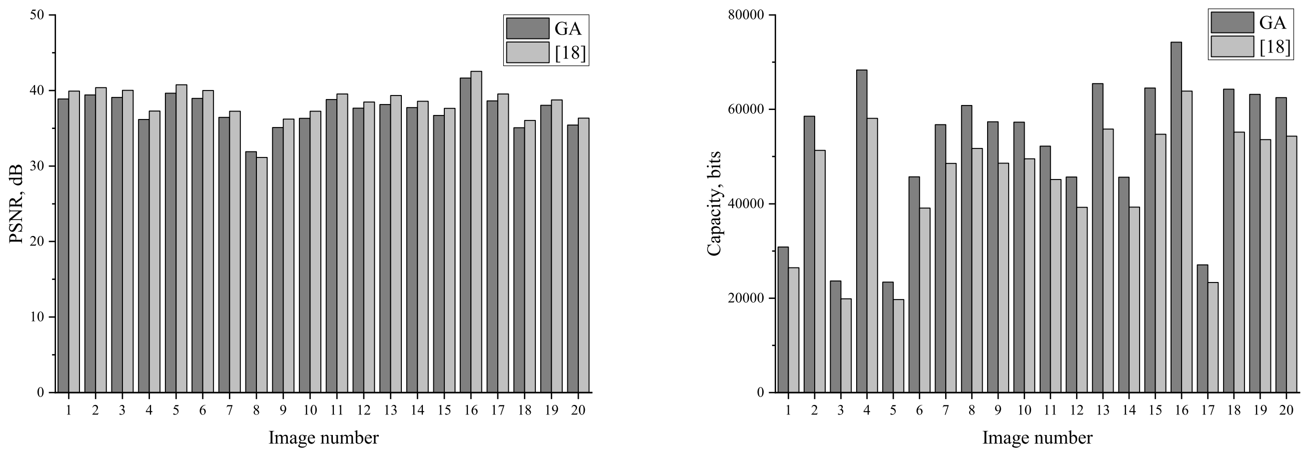
$$C_f = \frac{C_{block}}{C_{max}}. \tag{6}$$

There are different approaches to assessing the invisibility of embedding information. Invisibility can mean the absence of visible distortions of the stego image or resistance to steganalysis. Visual imperceptibility metrics show the level of difference between images before and after embedding. Resistance to steganalysis means that the cover image and the stego image are statistically indistinguishable. In this study, we demonstrate the achievement of visual imperceptibility as part of the objective function. We use the Peak Signal-to-Noise Ratio (PSNR), as this is the most common metric for image steganography research. In the course of subsequent research, we plan to create objective functions of a more complex type aimed at increasing the resistance to steganalysis.

For a block of 8 × 8 pixels, PSNR value is calculated by the formula

$$PSNR\text{ (dB)} = 10\log_{10}\left(\frac{255^2}{MSE}\right), \tag{7}$$

$$MSE = \frac{1}{64}\sum_{i=1}^{64}(I_i - S_i)^2, \tag{8}$$



(a)

(b)

Fig. 1. Indicators of the embedding effectiveness when using GA: (a) PSNR; (b) capacity.

where I_i is the intensity of pixel in the cover image block, S_i is the intensity of pixel in the stego image block.

It is impossible to know the maximum possible value $PSNR_{max}$ for a particular image in advance. However, empirical research has shown that the value for each block $PSNR_{block}$ does not exceed 60 dB in practice, so $PSNR_{max} = 60$ dB. The imperceptibility component is as follows:

$$C_f = \frac{PSNR_{block}}{PSNR_{max}}. \tag{9}$$

To preserve the main feature of the [18] algorithm, it is necessary to ensure error-free information extraction from the image block. To do this, we use E_f value:

$$E_f = \begin{cases} 1, & \text{if there are no errors;} \\ 0, & \text{if there are any errors.} \end{cases} \tag{10}$$

It is worth noting that the importance of the objective function components is not the same. Therefore, it is necessary to use weighting factors. Thus, the objective function is as follows:

$$F = k_C C_f + k_{PSNR} PSNR_f + k_E E_f, \tag{11}$$

where k_C is a capacity weighting factor, k_{PSNR} is an imperceptibility weighting factor, k_E is an error checking weighting factor, $F \in (0; 1]$.

Error-free information extraction takes precedence over high imperceptibility and capacity. If error-free extraction is not achieved in a given number of iterations, then the block becomes empty, so $k_E = 0.5$. $F < 0.5$ means that the extraction is not error-free. The weighting factors k_C and k_{PSNR} are selected empirically, taking into account the purpose of steganographic embedding. We use $k_C = 0.1$ and $k_{PSNR} = 0.4$ in our experiments.

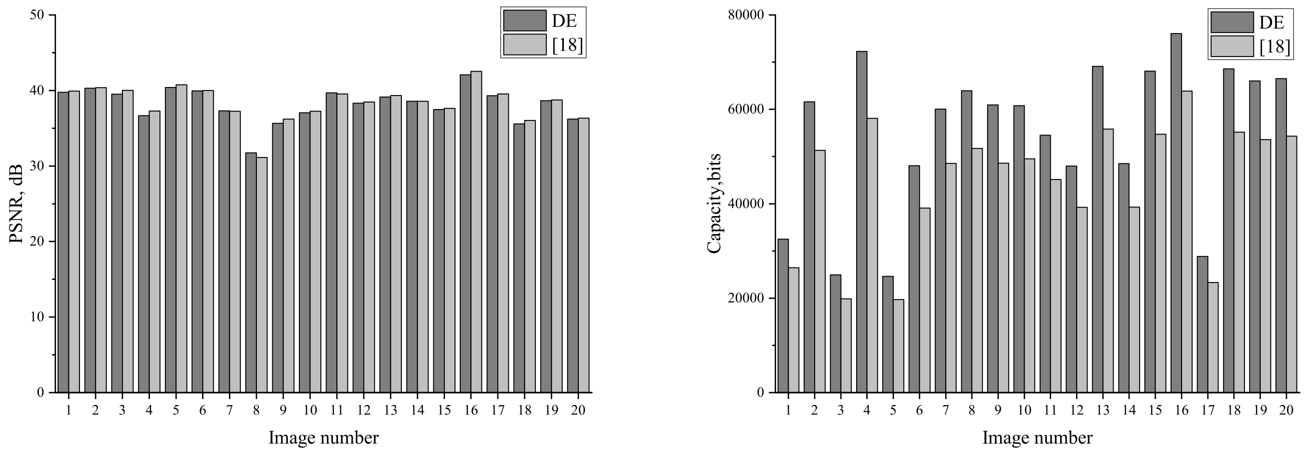
V. Experimental results and discussion

We conducted a series of experiments to evaluate the effectiveness of optimization for solving our problem. For the experiments we used 20 default grayscale 512 × 512 pixel images such as ”Airplane”, ”Lena”, ”Baboon”, etc. All images were in PNG format. During the experiments, we embedded as much information as possible into the image and measured the PSNR value for the entire cover image and stego image. We compared the results obtained with the previous version of our algorithm presented in [18].

It was empirically found that with a population size of about 40 individuals and reaching 30-50 generations (depending on the specific algorithm and image), the increase in PSNR and capacity values significantly slows down. Therefore, in all experiments, the population size was 40 individuals, and the optimization process continued for 40 generations, while the embedding was performed within 5 iterations. The best values of the parameters of the optimization algorithms were chosen experimentally. The limited volume of this paper does not allow us to provide detailed information on the choice of parameters, however, we indicate specific values in the description of each experiment.

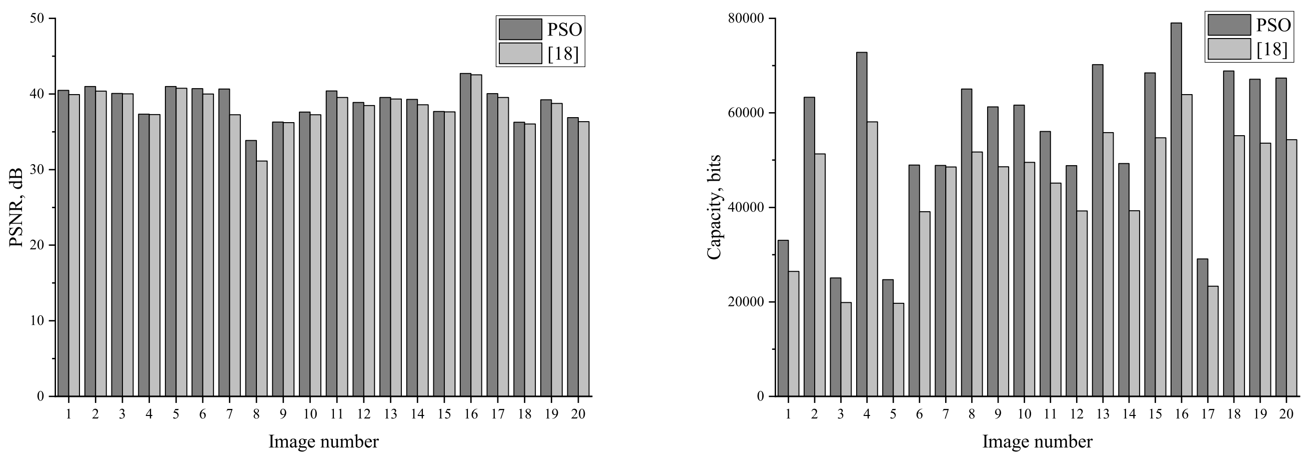
We have assessed the effectiveness of GA for solving our problem. We used the following GA parameters: $p_{cross}^{GA} = 0.8$, $p_{mut} = 0.05$. Fig. 1(a) and Fig. 1(b) show the PSNR and capacity values for different images, respectively. As the figures show, the use of GA leads to a decrease in the imperceptibility of embedding. The PSNR value decreased by an average of 2.20%. At the same time, the capacity increases by an average of 16.81%.

The next experiment was aimed at assessing the efficiency of DE. Algorithm parameters are $\alpha = 0.2$, and $p_{cross}^{DE} = 0.6$. Fig. 2(a) and Fig. 2(b) show PSNR and capacity values. The embedding imperceptibility has slightly degraded compared to the earlier version of the algorithm. On average, the PSNR value decreased by 0.44%. However, the use of DE had a



(a) (b)

Fig. 2. Indicators of the embedding effectiveness when using DE: (a) PSNR; (b) capacity.



(a) (b)

Fig. 3. Indicators of the embedding effectiveness when using PSO: (a) PSNR; (b) capacity.

significant positive effect on the embedding capacity. The increase in capacity averaged 23.18%. DE is a more effective solution for increasing the capacity of iterative embedding of information into the DFT phase spectrum than GA.

At the third stage of our research, we performed similar experiments with the PSO algorithm. We used the following algorithm parameters: $w = 0.7$, $\psi_p = 1.4$, $\psi_g = 1.4$. Fig. 3(a) shows the obtained PSNR values for different images, Fig. 3(b) shows the corresponding capacity values. The experimental results demonstrate the high efficiency of the PSO algorithm for adaptive embedding of information into the DFT phase spectrum. There is an increase in PSNR and capacity in all cases. The PSNR value increases on average by 1.77%. The growth in the number of embedded bits is significant, the capacity value increases on average by 23.73%.

Based on the results of the experiments, the following may be noted:

- Among the considered examples of metaheuristic optimization algorithms, the best results for improving the quality of adaptive embedding of information into the DFT phase spectrum were demonstrated by the PSO algorithm. GA is the worst suited for solving our problem.
- The lower efficiency of GA in comparison with DE and PSO allows us to conclude that the use of real number vectors is more efficient than binary vectors. This is due to the fact that in the case of using DE and PSO, as new generations are formed, the phase values after embedding approach those that were before embedding. GA finds the best positioning of the message bits in the block of DFT coefficients, however, it does not control the change in phase values.
- Despite the fact that the imperceptibility component has a greater weighting factor, there is a greater increase in capacity than the PSNR value. This allows us to conclude that changing each element of the phase spectrum worsens the imperceptibility of embedding, in contrast

to changing only those values that initially fall into the extraction intervals [18]. However, the results of experiments with the PSO algorithm show that even with a change in all phase values of the block, it is possible to obtain high indices of imperceptibility.

VI. Conclusion

Adaptive embedding of information into digital images is a promising direction in image steganography. In this paper, we investigated the applicability of some metaheuristic optimization algorithms to improve the efficiency of adaptive embedding of information in the DFT phase spectrum. Optimization algorithms allow us to find the best arrangement of a secret message fragment in an image block and provide high capacity and imperceptibility. According to the results of the experiments, it was shown that GA is not suitable for solving this optimization problem due to the use of binary vectors as individuals of the population. DE demonstrated good results. PSO provides a simultaneous increase in the PSNR value and the embedding capacity. This conclusion indicates the feasibility of studying the applicability of other optimization algorithms working with vectors of real numbers for solving this problem.

In this study, we used the PSNR metric as an indicator of the visual imperceptibility of embedding information in digital images. In the future, we are going to consider other metrics for assessing the invisibility of embedding and use them to construct the objective function. A promising research area is the development of a more complex objective function to achieve not only visual invisibility of embedding, but also statistical one. Thus, the extended objective function will ensure the embedding resistance to steganalysis methods.

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