

Hiding traces of double compression in JPEG images based on Tabu Search

Shen Wang · Xiamu Niu

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Abstract With the development of digital forensic techniques, the image disguise (also called image tampering or image manipulation) is challenged greatly. When the tampered JPEG image is saved, it was re-compressed. This progress causes radical change in the histogram of the discrete cosine transformation (DCT) coefficients. The amounts of some coefficient values decrease greatly or even disappear. It is easily to detect this pattern by statistics methods. To remove the fragility of image disguise, we need to revise the abnormal distribution of DCT coefficients. But random change in the coefficient values degrades the image quality. So we established an image disguising evaluation model aims at the JPEG recompression detection which can be solved by Tabu Search algorithm. Under the restraint of the evaluation model, the traces of double compression are removed, and the image quality is well preserved.

Keywords Image disguise · Double compression · Evaluation model · Tabu Search

1 Introduction

With powerful photo-editing software, image manipulation becomes very common in digital image processing. This method is indeed used to make forgery. But sometimes it is a usable way to insure the transmission security of images [1]. The scheme of the strategy is illustrated in Fig. 1. It shows an image that includes some secret content (the

character “A” and the word “laser”). Then, the regions are replaced with some unsuspecting content by image disguise method. The secret content is compressed and embedded into the image as a message. In order to guarantee good visual effect, the positions for data embedding are the rest areas except for inpainted regions. The receiver extracts the message and recovers the original image. Traditionally, steganography [2–4] and encryption [5] are used to ensure the confidentiality for image transmissions. Compared with image encryption that is the most common strategy for secure image transmissions, image disguise can exhibit higher secrecy. In image encryption, the secret region of the image is scrambled into a random pattern which cannot reveal any visual appearance of the secret region. However, the scrambled region implies the existence of the secret information in the image, which has the risk of being cracked by the adversary. While in image disguise, the secret region is concealed by replacing it with some unsuspecting content so that the disguised image is still visually plausible. In this regard, image disguise outperforms the encryption-based strategy in terms of the secrecy. In traditional steganography methods, all pixels of an image are embedded in the cover image to be transferred secretly and securely. In image disguise, the sensitive parts of the image are replaced. Then, the sensitive parts are embedded into the carrier. The disguised image is transferred in the public channel and will not be suspected. Because only the sensitive parts are embedded into cover image, the cover image can be used to transfer more secret images. It will become a feasible way for secret communication, if the disguise is undetectable by image forensic. The goal of digital image forensic is to detect the existence of image tampering or steganography. Some methods need to embed a mark into the original image or extract some information from it, for example, digital watermarking [6, 7]

S. Wang (✉) · X. Niu
Harbin Institute of Technology, Harbin 150001, China
e-mail: shen.wang@hit.edu.cn

X. Niu
e-mail: xm.niu@hit.edu.cn

and perceptual hashing [8, 9]. The blind forensic is based on the traces in the image introduced by the manipulation. To deal with tamper detection, some algorithms have been proposed. It is observed in [10] that image interpolation will introduce periodic correlations between pixels. On the basis of this fact, Popescu et al. propose to detect the trace of image tampering by evaluating the correlation between neighboring pixels with the aid of the EM (Expectation Maximization) algorithm. The lighting direction is also exploited as a clue for image forensic in [11], as it is difficult to maintain the consistencies in lighting directions of the regions from different source images. However, the lighting direction-based scheme is not applied to manipulations where the lighting direction is kept unchanged, such as duplication. The basic detection method of duplication is based on brute-search [12]. In order to enhance the robustness of image forensic against noise and compression, the PCA algorithm is employed to generate a coarse representation of the image [13]. The practical image disguise is done by image processing software, for example, Photoshop. It is difficult to control the quality factor precisely in the software, because the implementation of JPEG compression algorithm varies from one software to another. Thus, recompression using different quality factor is very common in image disguise. For JPEG images, the double compression is a vulnerability to the digital forensic. If we use different quality factor in double compression, the decreasing of coefficient values makes the histogram become periodic (If we use same quality factor in double compression, the periodicity in the histogram of the discrete cosine transformation (DCT) coefficients will not occurred. But because of the rounding operation in the JPEG compression procedure, there are also detectable differences between the distributions of the original image and the re-compressed image.). Fridrich et al. proposed a method to reveal this effect. To enhance the security of image disguise, we established an image disguising evaluation model aims at the JPEG recompression detection and solved it by using of Tabu Search algorithm. The gap in the histogram of DCT coefficient is filled by the adjustment. Our algorithm achieves good balance between security and image quality.

The rest of this paper is organized as follows. In Sect. 2, the proposed disguise method is elaborated. Experimental results are presented in Sect. 3 to demonstrate the effectiveness of the proposed work. Finally, this paper is concluded in Sect. 4.

2 Proposed algorithm

In this section, the JPEG recompression of image is introduced firstly. Then, the image disguising evaluation model is established in Sect. 2.2. Section 2.3 provides the solving method of this model.

2.1 Double compression detection of JPEG image

The quantization process transforms the continuous DCT coefficient values to discrete ones. Let S_1 denotes the quantization step used in the JPEG compression, the discrete coefficient values are considered as $N_i = i \times S_1$, where i is the quantized value. In nature image, the distribution of quantized values is considered as Laplacian distribution. In the re-compression process, assume that the quantization step S_2 is chosen. Then, $N_i = \left[i \times \frac{S_1}{S_2} \right]$, where $[]$ means the rounding operation. If S_1 is multiple of S_2 , the values of i are discrete integers. It means that the histogram of quantized values is periodic. Some bans disappear, and the positions become gaps (shown in Fig. 2a, b). Figure 2a and b show the histograms of the DCT coefficients extracted from the original and the re-compressed JPEG images, respectively. Even S_1 is multiple of S_2 , and the distribution of quantized values is much different from Laplacian distribution. We use the following instance to illustrate the phenomenon in double JPEG compression. We take a vector composed of consecutive numbers as the example of the original signal, $S = \{s(i)|s(i) = i, i = 1, 2, \dots, 20\}$. We first quantize the original signal S by a step size of 4, and the quantization result is $S_1 = \text{round}(S/4) = [01111222233334444555]$. To simulate the case in double JPEG compression, the signal is consequently reconstructed and quantized by a new step size. The reconstructed signal can

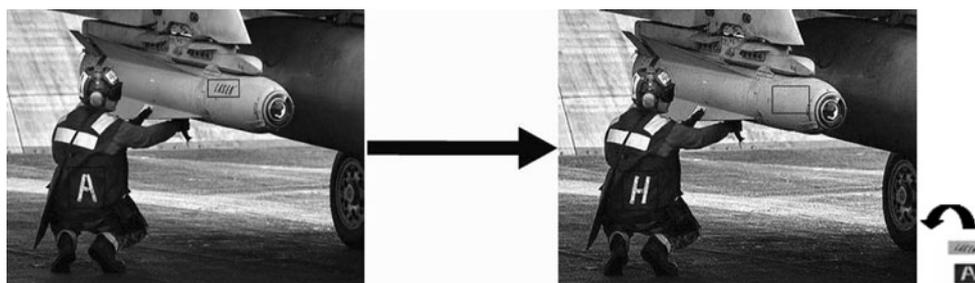


Fig. 1 The scheme of image disguise

be obtained by multiplying the quantization result by the initial step size, as $S_2 = 4 \times S_1 = [0444488881212121216161616202020]$. After quantizing S_2 by a new step size of three, we can get $S_3 = \text{round}(S_2/3) = [01111333344445555777]$. It can be found that the values of 2 and 6 are replaced by others after double compressions. In Fridrich's forensic algorithm, the abnormal histogram is compared with the standard distribution, and double compression is revealed [14].

2.2 Evaluation model for image disguise

For image disguise, there are two conflicting objectives: *image security* and *image quality*. Thus, the evaluation model is composed by two parts: the goodness of fit and perceptual distance.

The variation of DCT coefficients is the foundation of the evaluation on the image quality by Watson model. So the perceptual distance is calculated by the Watson's perceptual error metric [15]. This model is based on DCT coefficient errors. Considering the visual pattern, the errors are revised into the actual perceptual variation, called perceptual distance via (1). A smaller D (perceptual distance) means better image quality.

$$D_{\text{wat}}(x, x^w) = \left(\sum_{i,j,k} \left| \frac{e_{ij}^k}{s_{ij}^k} \right|^p \right)^{\frac{1}{p}} \tag{1}$$

where $e_{ij}^k = (X_{ij}^k)^w - X_{ij}^k$ denotes the DCT coefficient errors between the original image and the degrading image. X_{ij}^k denotes the coefficient of frequency i, j in the k th block. s_{ij}^k is the contrast masking threshold with the form (2)

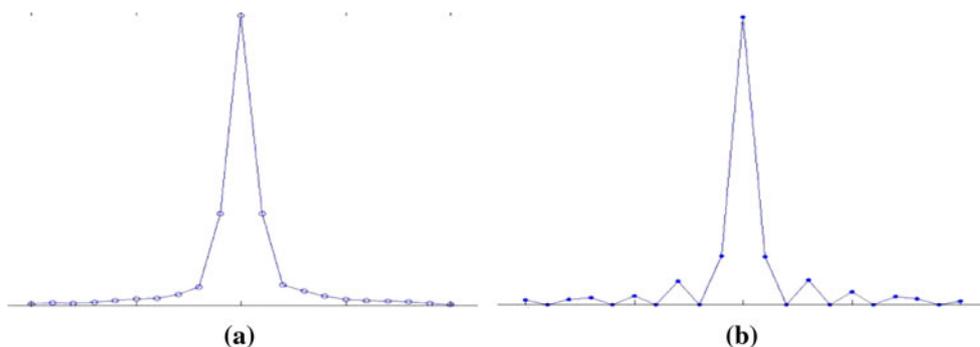
$$s_{ij}^k = \max \left\{ t_{ij}^{kL}, |X_{ij}^k|^{\beta_{ij}} \cdot (t_{ij}^{kL})^{1-\beta_{ij}} \right\} \tag{2}$$

where the luminance masking threshold as the Eq. 3

$$t_{ij}^{kL} = t_{ij}(X_{00}^k/\bar{X})^{\alpha_T} \tag{3}$$

where X_{00}^k is the DCT coefficient in k th block. \bar{X} denotes the mean value of the image. t_{ij} is the sensitivity of i, j frequency band.

Fig. 2 a The distribution of quantized DCT coefficients of original image; **b** the distribution of re-compressed image



The other part of the evaluation model measures how well the distribution of the DCT coefficients fits the Laplacian distribution [16] (Eq. 4). μ is the parameter of the Laplacian distribution. It is estimated by the original image. When the DCT coefficients are adjusted, the distribution of the result should be similar to the original one.

$$p(x) = \frac{\mu}{2} \exp\{-\mu|x|\} \tag{4}$$

In this paper, we measure the goodness of fit by Pearson's chi-square test. First, we assume that the frequency of DCT coefficients has a form of Laplacian distribution. Thus, the parameter of Laplacian distribution can be estimated by maximum likelihood estimation. The likelihood function is

$$L(\mu) = \left(\frac{\mu}{2}\right)^n \exp\left\{-\mu \sum_{i=-n}^n |x_i|\right\} \tag{5}$$

where x_i is the value of each DCT coefficient. The maximum of $L(u)$ is the solution of Eq. 6.

$$\frac{d}{d\mu} \ln L(\mu) = \frac{n}{\mu} - \mu \sum_{i=-n}^n |x_i| = 0 \tag{6}$$

Then, the parameter u is determined by the expression (7).

$$\mu = \frac{n}{\sum_{i=-n}^n x_i} = \frac{n}{\sum_{i=-n}^n |iN_i|} \tag{7}$$

where N_i is the amount of quantized DCT coefficients with the same value.

Secondly, we measure the difference between the distribution of DCT coefficients and the Laplacian distribution by chi-square statistics (Eq. 8).

$$\chi^2 = \sum_{i=-n}^n \frac{f_i^2}{np_i} - n \tag{8}$$

where f_i is the frequency of each DCT coefficient value, P_i is the theoretical frequency for the i th bin:

$$p_i = \int_{i-0.5}^{i+0.5} \frac{\mu}{2} \exp\left\{-\mu \sum_{i=-n}^n |x_i|\right\} dx \tag{9}$$

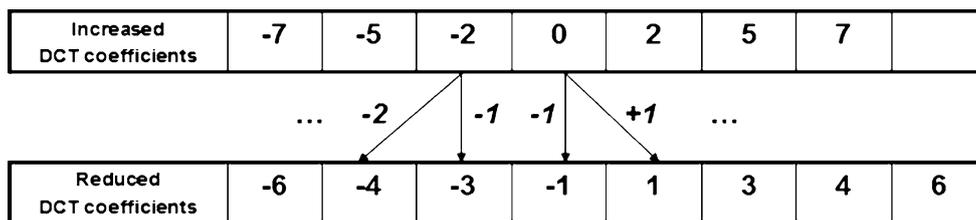


Fig. 3 The example of transition of DCT coefficients

Fig. 4 The result of DCT coefficients transiting

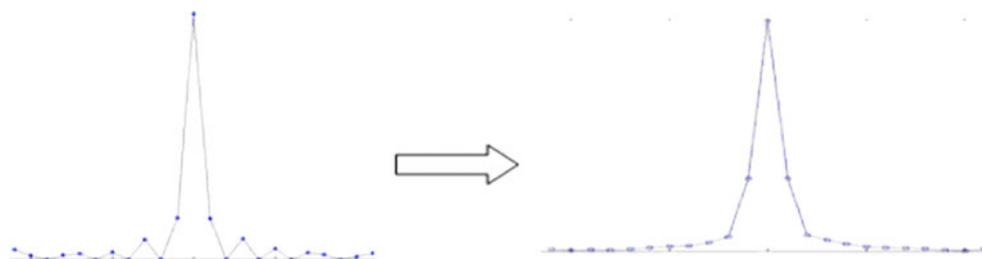
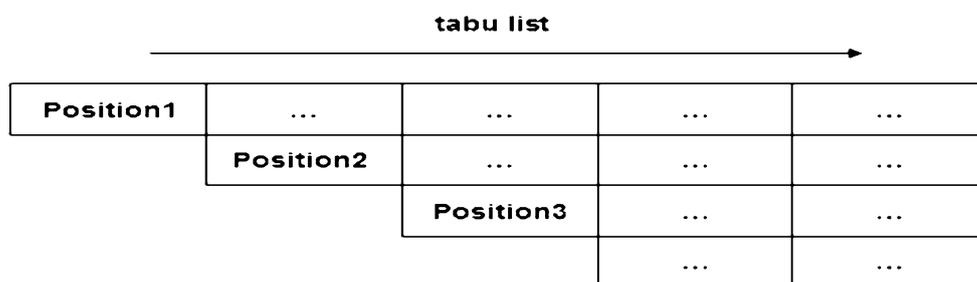


Fig. 5 Tabu list



The function of evaluation model Z (Eq. 10):

$$Z = \frac{1}{Q(D_{wat})} + S(\chi^2) \quad \text{if } \chi^2 < \chi_{0.05}^2 \quad (10)$$

In our algorithm, we adjust the DCT coefficients to recovery the Laplacian distribution. But random change in the coefficient values degrades the image quality. To balance the security and image quality, the optimal parameters μ and D are required. The calculated amount would be unacceptable if the exhaustive search is applied on an image with general size. So we chose the Tabu Search to optimize the adjustments.

2.3 Calculating of optimal parameters μ and perceptual distance D

Tabu Search is a heuristic optimization method to solve the combinatorial optimization problems [17, 18]. It enhances the performance of a local search method by using memory structures: Once a potential solution has been determined, it is marked as “tabu” so that the algorithm does not visit that possibility repeatedly. To achieve best result, “aspiration criteria” is introduced: These override a solution’s tabu state, thereby including the otherwise-excluded

solution in the allowed set. Tabu Search includes following steps.

- Step 1. Set the length of the tabu list and stopping criterion and generate x_i randomly as initial solution set.
- Step 2. Adjust the solutions x_i to x'_i in the neighborhood of x_i and move x_i to the tabu list.
- Step 3. If x'_i satisfy the aspiration criteria, take x'_i as the best solution.
- Step 4. If the stopping criterion is satisfied, stop the process, otherwise go to step 2.

When the DCT coefficients are adjusted, we use the tabu to achieve the tradeoff between the security and image quality. The procedure includes the following steps:

1. Estimate the parameters of DCT coefficients in the original image.
2. Construct the empty tabu list for each DCT coefficient.
3. Determine the amount X_{ij} of DCT values to be adjusted (shown in Figs. 3, 4). Let D_i denotes the set of DCT coefficients with the value i . X_{ij} denotes the amount of coefficients which change from D_i to D_j . For each value i ,

$$x_i = \sum_j x_{ij}$$

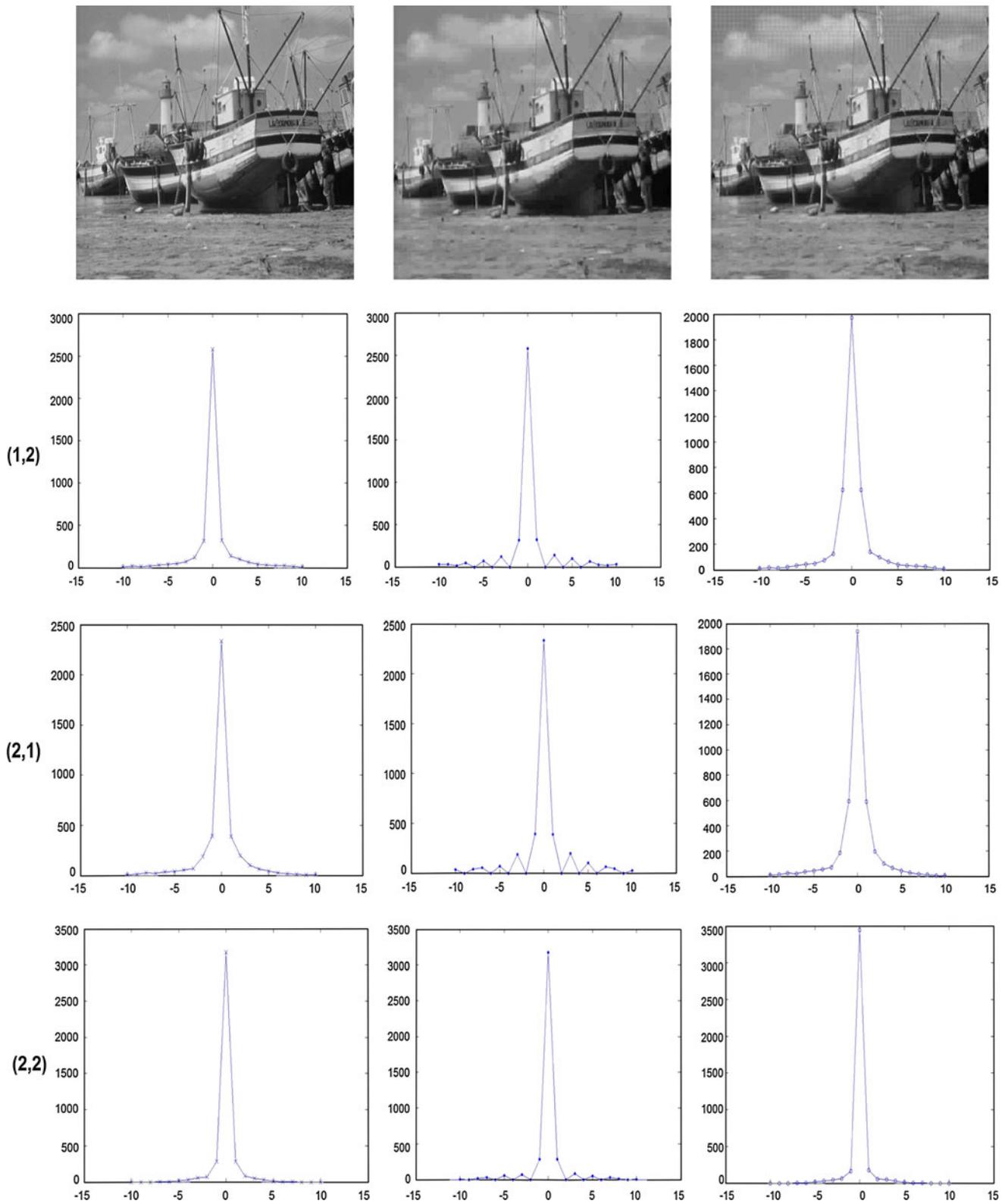


Fig. 6 The first column shows, respectively, the original image, re-compressed image with quality factors 20–90, and the optimized image by Tabu Search. The following columns show the corresponding histograms of DCT coefficient of each image

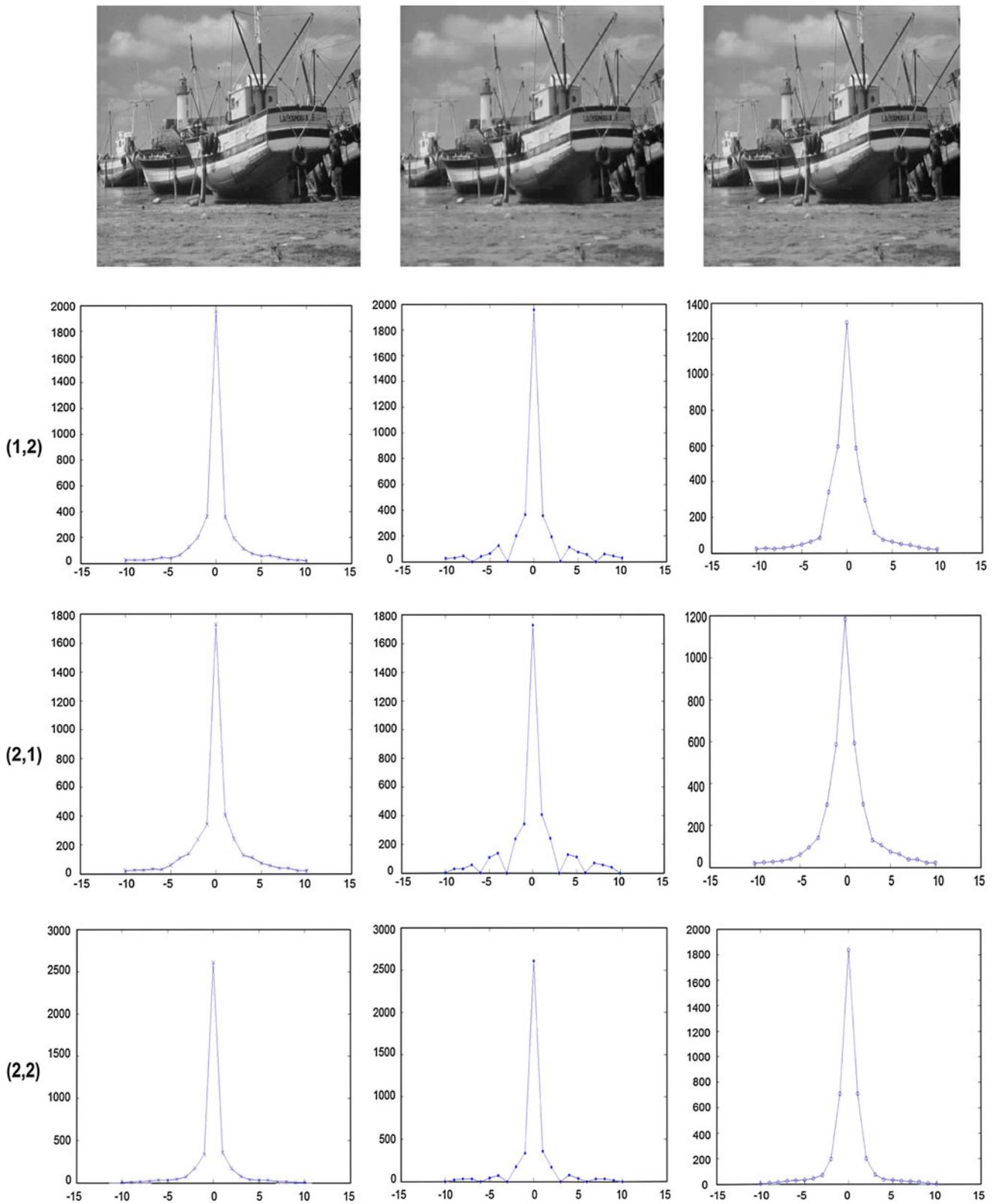


Fig. 7 The first column shows, respectively, the original image, re-compressed image with quality factors 90–50 and the optimized image by Tabu Search. The following columns show the corresponding histograms of DCT coefficient of each image

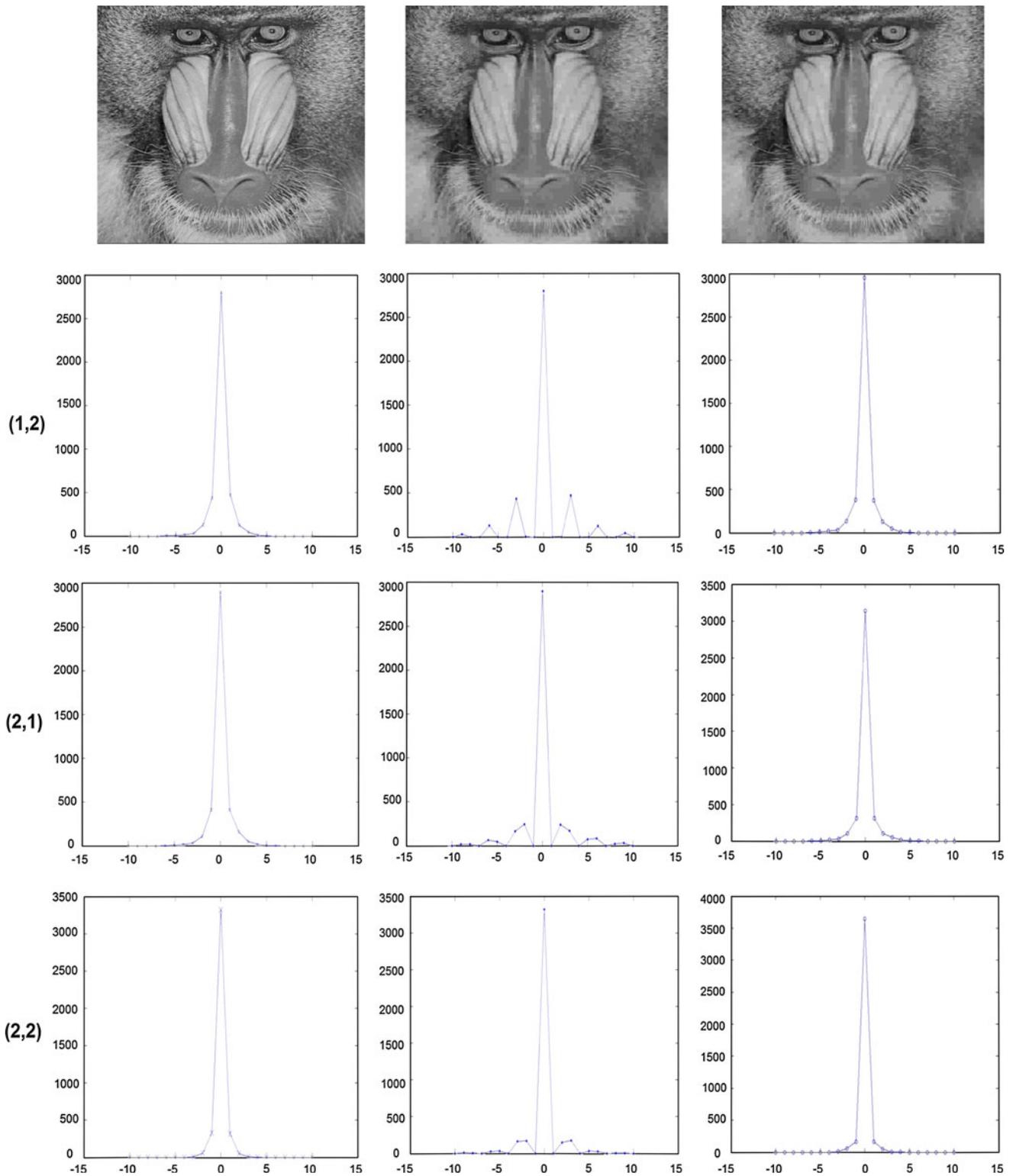


Fig. 8 The first column shows, respectively, the original image, re-compressed image with quality factor 10–30 and the optimized image by Tabu Search. The following columns show the corresponding histograms of DCT coefficient of each image

denotes the amount of coefficients in D_i to be changed. Select X_{ij} coefficients from each D_j randomly, unless j is not in the tabu list of this coefficient.

4. Adjust the coefficients to fill the gaps in the DCT coefficients histogram.
5. Put the current value of each DCT coefficient into tabu list (shown in Fig. 5).
6. Check the distribution of the disguise image. If the distribution follows Laplacian distribution and the image quality is better than last iteration, save this image as the best solution.
7. Repeat steps 4–6 iteratively until the stopping criterion is satisfied.

3 Results analysis

To test the performance of the proposed algorithm, three groups' experiences are applied to two images. The two test samples are 512×512 gray images. The first round experience is to compress the "fishingboat" image by quality factors 20 and 90 separately. The second-round experience compresses the "fishingboat" image by quality factors 90 and 50 separately. And the third-round experience is for the "baboon" image, and the quality factors are 10 and 30. The Tabu Search algorithm is applied to each image. The stopping criterion is 10,000 iterations. By the experiences on a lot of images, we find that the histogram of positions (1, 2), (2, 1), and (2, 2) of DCT coefficient matrixes of each image can express the variation of the statistic character between and after compression. The following three figures illustrate the indication.

In the first-group experience (shown in Fig. 6), the image is compressed with quality factor 20 and re-compressed with quality factor 90. Some of the coefficients of DCT histogram of re-compressed image reduce or disappear periodically. By parameter estimation method, the parameters of position (1, 2), (2, 1), and (2, 2) in the DCT coefficient matrix of original image are $\mu = 1.01$, $\mu = 0.95$, and $\mu = 2.53$. While the method proposed in this paper eliminate this phenomenon. The perceptual distance in Watson model is $D = 124$.

In the second-group experience (shown in Fig. 7), the image is compressed with quality factor 90 and re-compressed with quality factor 50. Some of the coefficients of DCT histogram of re-compressed image also reduce or disappear periodically. By parameter estimation method, the parameters of position (1, 2), (2, 1), and (2, 2) in the DCT coefficient matrix of original image are $\mu = 0.68$, $\mu = 0.61$, and $\mu = 1.17$, while the method proposed in this paper eliminates this phenomenon. The perceptual distance in Watson model is $D = 163$.

In the third-group experience (shown in Fig. 8), the image is compressed with quality factor 10 and re-compressed with quality factor 30. Some of the coefficients of DCT histogram of re-compressed image also reduce or disappear periodically. By parameter estimation method, the parameters of position (1, 2), (2, 1), and (2, 2) in the DCT coefficient matrix of original image are $\mu = 2.18$, $\mu = 2.32$, and $\mu = 4.43$, while the method proposed in this paper eliminates this phenomenon. The perceptual distance in Watson model is $D = 53$.

The experimental results prove that our algorithm can eliminate the trace of double compression effectively. To show the periodicity in the histogram obviously, we choose small quality factors. The high compression ratio causes the degrading of the image quality in experiment 1. Indeed, the perceptual distance between the original image and the compressed version with quality factor 20 is 96. In experiment 2, the perceptual distance in Watson model looks bigger than expected. It shows a puzzling phenomenon. If the image is re-compressed both with relatively high-quality factors, more search is needed to find a good resolution preserving the image quality. But we set the same searching steps for each experiment to compare the results explicitly. Fortunately, a rather good resolution is found in experiment 3. It shows the efficiency of our algorithm.

4 Conclusion

Re-compression is a common operation in image disguise. To eliminate the insecure statistic features, this paper proposed an image disguising evaluation model aims at the JPEG recompression detection and calculated the optimal parameters μ and D by Tabu Search algorithm. By this method, the security and visual quality of image achieve a well balance. The experimental results show our method may disguise an image more securely and effectively. After recompression, the "gap" will occurred in the histogram of the DCT coefficients due to rounding. Thus, our algorithm is feasible to any natural images. In future, more works should be devoted to improve the stableness of this algorithm.

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