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A Novel Reversible Data Hiding Method for Color Images Based on Dynamic Payload Partition and Cross-Channel Correlation

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Abstract. *The traditional color image reversible data hiding (RDH) techniques mainly focus on utilizing inter-channel correlations to improve embedding performance, but mostly have poor time efficiency. Nevertheless, the information redundancy in the color image is not fully exploited. In this paper, a new sorting strategy and a payload partition scheme are proposed. Thus, a novel RDH method for color images is proposed based on existed PEE algorithm. Extensive experimental results demonstrate that the proposed method achieves better performance comprehensively considering distortion control and time efficiency than prior state-of-the-art methods.*
Keywords: Reversible data hiding, Prediction-error expansion, Payload partition, Cross-channel correlation

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1. **Introduction.** Data hiding is a technique to conceal secret message into a multimedia carrier, such as image, audio, or video. Watermarking and steganography respectively concerned about the robustness and the invisibility of hidden data are derived from data hiding, which can be widely utilized for copyright protection, content authentication, and media asset management [1–5].

However, most of the existing data hiding methods may cause permanent damage for the original carrier in the data embedding process, and thus they are not suitable for some special applications, such as military field where any permanent distortion to the original content is unacceptable. To this end, reversible data hiding (RDH) has been proposed to recover completely the original content of the the marked carriers after embedded message is extracted. Nowadays, research on RDH has become quite important, as it occupies an important place in copyright protection and data hiding of sensitive images, such as military and medical images.

Early RDH methods are mainly based on loss-less compression [6–10]. This method will compress a part of cover image and embed data in the saved space. J. Fridrich et al. [6] proposed a RDH method compressing the least significant bit (LSB) plane of an image with the minimal redundancy to make embedding space. M. U. Celik et al. [7] proposed a generalized LSB compression for RDH, which introduces additional operating points on the capacity-distortion curve and utilizes unaltered portions of the host signal as side-information to improve the compression efficiency and the loss-less data-embedding capacity. However, the compression may cause a large alteration on pixels. Whats more, the bit-plane correlation limits the efficiency of the loss-less compression RDH approaches. So, early compression-based RDH may not provide satisfactory performance. W. Zhang et al. [8,9] introduced recursive compression to current techniques and obtained a significant improvement. The spatial quad-based data embedding exhibits better performance than M. U. Celik's algorithm. A. M. Alattar. [10] introduced a reversible integer transform-based RDH with low image distortion.

Another important RDH technique is called histogram shifting [11–16], as histogram bins are shifted to vacate an empty bin for data embedding. In 2006, Z. Ni [11] proposed a histogram shifting method based on the pixel-intensity histogram. They select a pair of peak and zero points from the histogram of the cover image to carry message. Pixels between peak and zero points in the histogram will be modified to save space for peak points during embedding process. As the pixels of cover image will be modified 1 at most, histogram shifting guaranteed less distortion compare to loss-less compression. However, the embedding capacity is limited by the number of pixels present in the peak point in the histogram. C. C. Lin et al. [12] presented a multilevel reversible watermarking approach that utilizes the histogram of difference image. Y. Y. Tsai et al. [13] constructed the difference histogram by calculating the differences between a pixel and its left and upper neighbors. P. Tsai et al. [14] proposed a subtly different approach which the difference between a basic pixel and every other pixel in the block instead of adjacent pixels is used. Z Ni et al. [15] used modulo-256 addition to solve overflow and underflow problems.

In 2003, J. Tian [17] proposed a novel a reversible data hiding method named difference expansion, a significant spatial domain algorithm performed on pixel pairs. In this method, they partitioned the cover image into pixel pairs, expanded the difference between two adjacent pixels two times and then embedded a message bit into the LSB of the expanded difference. In case of overflow or underflow, the location map was used to identify embedded pixels with one bit for each pair of pixels. The location map is loss-less compressed and embedded into the image. Thus, the redundancy in the digital images is utilized to achieve higher embedding capacity and low distortion.

One of the illustrious extensions to the DE scheme is the prediction-error expansion (PEE). D. M. Thodi and J. J. Rodrguez. [18] improved Tian's method by replacing the pixel difference with prediction error based on the correlation among the neighboring pixels. PEE uses the prediction-error histogram (PEH) which is sharper than the intensity histogram, so a much higher capacity can be obtained compare to histogram shifting under the same condition of modifications. Since PEE exploits more correlations in an image, it has an excellent performance in terms of capacity and distortion control.

In 2009, H. W. Tseng et al. [20] computed the predictive value by using various predictors and reported a simple reversible watermarking approach exploiting the expansion of the difference between a pixel and its predictive value. Y. Hu et al. [21] eased the burden of recording the auxiliary information by utilizing an effective location map. V. Sachnev et al. [22] proposed a PEE based algorithm sorting the prediction-errors by the local variances, which significantly reduced the distortion compared to the techniques that employ direct raster scan in watermark embedding. M. Chen et al. [23] proposed accurate prediction by incorporating full context. X. Li et al. [24] augmented the global prediction error by adaptively embed two bits into a smooth pixel, which prevents the expansion of pixels whose prediction error is large, and thus achieved a very high capacity with the relatively low distortion. G. Coatrieux et al. [25] proposed a dynamic RDH method which adaptively identify the areas suitable for embedding, and can embed data even in a texture area. S. W. Weng. et al. [26] proposed a novel integer transform which can be considered as a prediction process, so that two bits are embedded into each of the $(n-1)$ pixels. Most of the state-of-the-art RDH algorithms like [20–31] were basically based on PEE and histogram shifting.

The existing RDH research mainly focused on gray-scale image, and there are only a few RDH works directly related to color image. For a color image, a vector consisting of three components (R, G, B), which are highly correlated with each other, is assigned to a pixel. Generally speaking, traditional RDH techniques regarding color image embed data into each color channel independently, but cannot provide an optimal solution as they ignore the inter-channel correlations. S. Lee et al. [31] proposed a color RDH method based on integer-to-integer wavelet transform, and embedded the data into three color channels separately. Most RDH algorithms like [22, 27] can also be used for color image in the same way. W. J. Yang et al. [28] proposed a RDH algorithm for color filter array image to achieve small prediction-errors in the color difference domain. J. Li et al. [29] proposed a RDH algorithm based on prediction-error expansion that can enhance the prediction accuracy, utilizing the similar edge structures between different channels. B. Ou et al. [30] proposed an RDH method for color images based on channel-dependent payload partition and adaptive embedding, which assign different sizes of payload into each channel instead of equally embedding. Nevertheless, the information redundancy existed in the color image is not fully exploited. Whats more, most existing RDH algorithms for color image utilizing inter-channel correlations have poor time efficiency as they always consider reducing distortion only. Thus, there is still a great potential for the further improvement on color images.

In this paper, a novel RDH method for color images is proposed based on dynamic payload partition and cross-channel correlation. The proposed method extended the traditional channel-dependent payload partition schemes and extremely improved the time efficiency. Inspired by Ou et al.' method, we assigned different sizes of payload into each channel as color channels have different embedding capacity. However, our method used greedy algorithm to get approximate optimal parameter, instead of exhaustive search whose computational complexity is unacceptable. Besides, a new sorting strategy for selection of data hiding position is proposed. As the prediction-errors across the channels are highly related, the prediction-errors in the reference channels like the smoothness of a pixel are also used to select data hiding position. In that way, both the total distortion and the computational complexity are effectively reduced. Extensive experimental results on standard images demonstrate that the proposed method can exploit the color images redundancy better and outperforms some state-of-the-art methods.

The rest of paper is organized as follows. Section 2 reviews traditional PEE method and existing payload partition scheme, makes an analysis for improvement, and presents the main idea of the proposed method. Section 3 describes the implementation of the proposed method, and gives detailed embedding and extracting algorithm. Section 4 gives the experimental results and the corresponding analysis. Finally, Section 5 concludes this paper.

2. **Main idea of the proposed method.** In this section, we will introduce the main idea of the method.First, we will review the traditional PEE method and the existing payload partition scheme proposed by Ou et al. [30], whose time efficiency will be analyzed. Then, a novel payload partition will be proposed based on the analysis. Finally, we will construct a more efficient sequence for distortion reduction utilizing the similarity of predict-errors on different channels.

2.1. **Traditional PEE method and the existing payload partition scheme.** Considering the data embedding process, traditional PEE method is consisted of the following sections:

First, the pixels in the cover image will be collected into a sequence $(p_1, p_2, ..., p_n)$,and sorted according to their corresponding characteristic such as smoothness.

Then, the prediction error histogram will be constructed. Each pixel in the sequence will be predicted by predictor utilizing the information redundancy, and prediction error will be calculated as

$$e_i = p_i - \lfloor \hat{p}_i + 0.5 \rfloor \tag{1}$$

Finally, the prediction error will be expanded for the insertion of the embedding message bit b.Two integers $T_l$and T_r, are defined to divide the prediction-error histogram into one inner region (IR) and two outer regions (OR). The prediction-errors e in the inner region and in the outer regions will be differently modified.

$$e'_i = \begin{cases} 2e_i + b & e_i \in [T_l, T_r) \\ e_i + T_l & e_i < T_l \\ e_i + T_r & e_i \geq T_r \end{cases} \tag{2}$$

where $b \in 0, 1$ is one to-be-embedded bit. After embedding, the marked pixel will be

$$p'_i = \lfloor \hat{p}_i + 0.5 \rfloor + e'_i \tag{3}$$

In order to simplify the problem, we define $T_l = -t$,$T_r = t$, thus

$$p'_i = \begin{cases} p_i + e_i + b & e_i \in [-t, t) \\ p_i - t & e_i < -t \\ p_i + t & e_i \geq t \end{cases} \tag{4}$$

Letting P_{IR} and P_{OR} represent the number of pixels used for embedding in inner (IR) and outer regions (OR). The distortion on the prediction-error sequence will be

$$D = P_{IR}(e + b)^2 + P_{OR}t^2, e \in [-t, t) \tag{5}$$

Obviously, P_{IR} represents the capacity of PEE method and the distortion is mainly determined by the number of pixels in outer regions P_{OR} and the modification threshold . The main objectives to enhance the performance of PEE based reversible techniques are making full use of embedding capacity under fixed threshold t and minimize P_{OR}, which is, letting pixels in inner region occupy the front position in the sequence.

On this basis, Ou et al. [30] proposed a payload partition scheme to construct an efficient sub-sequence satisfies the payload requirement while makes the length as short as possible by selecting the just enough low-energy prediction-errors. In this method, Ou et al. exhaustively search all the candidates for the optimal parameter determination. Ou et al also utilize the local and reference complexities to sort the sequence and prediction-errors in reference channel to control energy. For each possible partition scheme using each energy control threshold, all the pixels would be processed to estimate the distortion. Then all combinations of (EC_R, EC_G, EC_B) satisfying the capacity requirement will be considered, and the one with the shortest length of the triple sub-sequences will be chose as the optimal result which will be used in PEE afterwards.

However, as the parameter determination is required, the time cost of Ou et al method is much larger than traditional PEE method. As Ou et al. explained [30], the corresponded computational complexity is approximated as $O(K \times N)$, where N is the number of pixels and K is the number of candidates for payload partition. The smaller the step size and the smoother the image, the more time consumed for searching. Defining $R_{max}, G_{max}, B_{max}$ to represent the maximum capacity of each channel, the computational complexity of obtaining the estimation of the embedding distortion of each channel for different capacities was approximated as $O(R_{max}/step \times L \times N)$, where N is the quantity of pixels and L is the length of the value domain of energy control thresholds. The computational complexity of finding the minimum distortion was $O(R_{max} \times G_{max} \times B_{max})$. As we can see, although Ou et al method could get the optimal parameter determination, the time cost it caused is unacceptable.

2.2. **Proposed payload partition and adaptive embedding.**

2.2.1. *Sub-sequence construction.* Although correlated, the three RGB components of a pixel are not obviously close to each other in intensity but in the derived prediction-errors. Fig. 1 shows the histogram of the difference and prediction-errors between the red and green channels of image Lena. Where the predicted values $\hat{p}_i$ are simply obtained by rhombus predictor.

$$\hat{p}_i = \frac{p_i^w + p_i^s + p_i^n + p_i^e}{4} \tag{6}$$

Obviously the prediction-error histogram has a small variance. Since the three channels represent the same object, the corresponding edge information is usually similar. The prediction-errors reflect the edge information and are less affected by luminance. So the prediction-errors across the channels are usually close to each other, which can be considered as reference information to reduce distortion. Thus, a more efficient sequence could be constructed.

Traditional sub-sequence construction for gray images improves embedding performance by sorting the pixels according to their context smoothness Ω, which was presented by the local variance for their neighboring pixels [17]. And Ou et al. use the absolute sum of derivatives along directional changes in neighboring pixels [25].

$$\Omega = |p_i^n - p_i^s| + |p_i^w - p_i^e| + |p_i^n + p_i^e - p_i^s - p_i^w| + |p_i^w + p_i^s - p_i^e - p_i^n| \tag{7}$$

Since the prediction-errors cross channels are highly related, it helps to estimate the embeddable pixels. We use G to presents the information from reference channels, which is calculated as

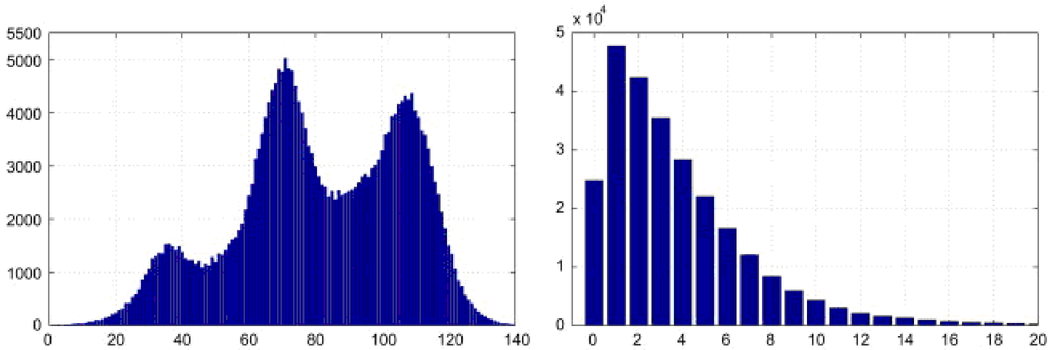

FIGURE 1. The histogram of the difference and prediction-errors between the red and green channels of image Lena

$$G = \frac{e_{r1}^2 + e_{r2}^2}{2} \tag{8}$$

where e_{r1}^2, e_{r21}^2 are the prediction-errors in the reference channel calculated in the same way.

In this paper, every pixel in the current channel is associated with a value C to improve our sorting strategy, which is calculated as

$$C = \Omega + G \tag{9}$$

By sorting the pixels according to the value C, both local complexity in current channel and the correlation cross channels were considered. As Fig. 2 shows, a more compact sub-sequence will be constructed for the same capacity

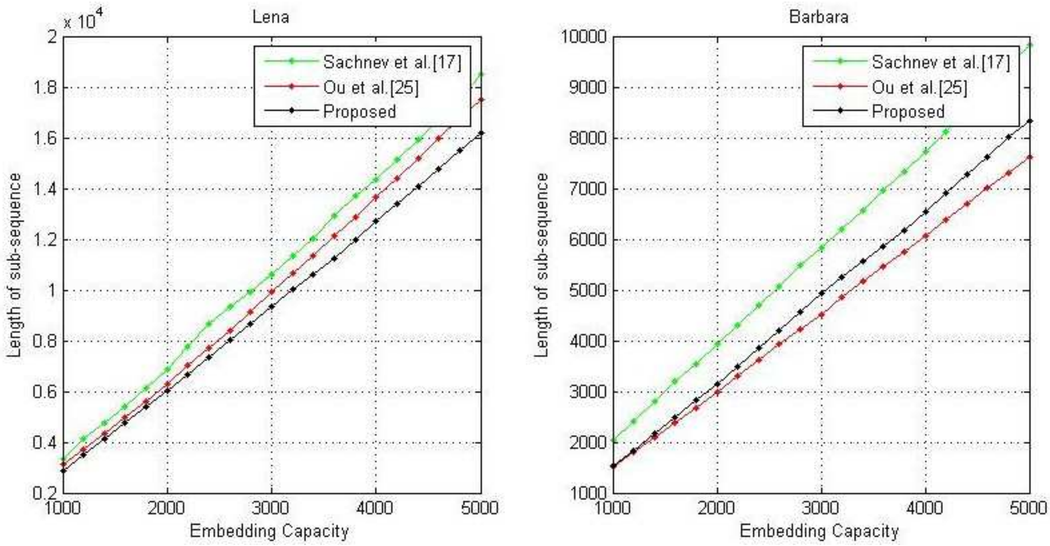

FIGURE 2. The length of sub-sequence for the green channel of Lena and Barbara

2.2.2. *Dynamic payload partition.* As it was proposed in (5), the embedding distortion is highly affected by the total length of the sub-sequence for a given capacity. The main purpose of dynamic payload partition is constructing a combination of the triple sub-sequences with the shortest length satisfying the capacity requirement.

Using the sub-sequence constructed above, we can distribute payload dynamically with better time efficient. As it shows in Fig. 3, after dividing the overall payload into fixed-payload segments, e.g. each segment contains 1000 message bits, we can calculate the length of the sub-sequence that each segment shares. As can be seen from Fig. 2, the sub-sequence length of each segment is approximately increasing. Thus we can use a greedy algorithm to find the approximate optimal result.

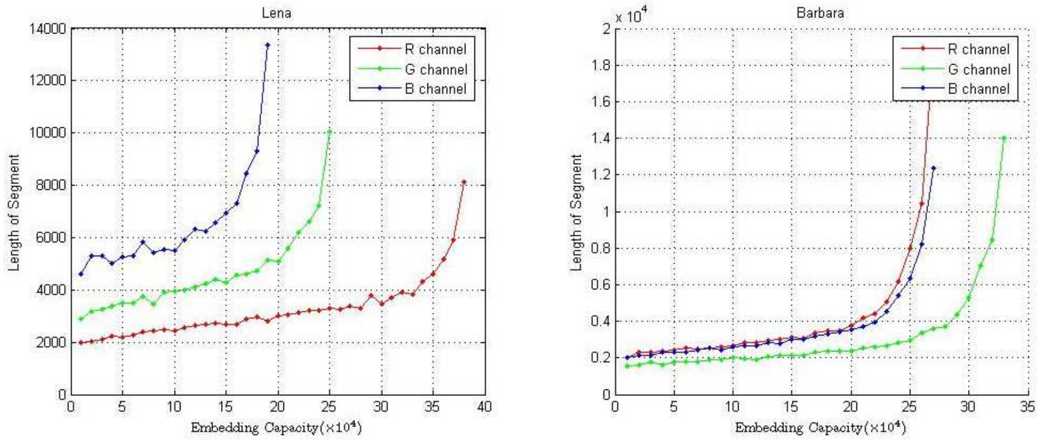

FIGURE 3. The length of segment carrying the fixed-payload in the sub-sequence for each channel

For a single channel, as the length of each carrier segment is approximately increasing, the optimal result of payload partition will be the sum of the segments occupies forward position in the sub-sequence. Thus the optimal result of payload partition will be the combination of the triple segment-sums for each channel satisfying the given capacity.

The main idea of the dynamic payload partition is to assign the payload message to the shortest segment until the given capacity is satisfied. The main procedures of the dynamic payload partition are described as follows.

Step1. Utilize the method proposed in 2.2.1 to construct the triple sub-sequences of each channel, separate and mark the prediction-errors in inner and outer regions of the PE histogram.

Step2. Divide all the payloads into fixed-size-payload segments and calculate the length of the sub-sequence that each segment shares. Let the to-be-embedded payloads for the three channels are EC_R, EC_G and EC_B which were initialized to zeroes.

Step3. Take the length of fixed-size-payload as step length. Find the minimum value of S_R, S_G and S_B, which present the length of segment occupy the first position in the sub-sequence, the fixed-length payload will be assigned to the corresponding channel and then the corresponding S will present the following segment in the sub- sequence.

Step4. Step 3 is iteratively operated until the predefined payload is achieved.

3. **The proposed method.** In this part, we will present detail data hiding algorithm for color image, based on our proposed dynamic payload partition and prediction-error expansion.

As shown in Fig. 4, while we hide data into one channels, the other two channels will be taken as the reference channel, regardless of the reference channel have been marked or not, which ensured the consistency of information on both the encoder and the decoder. Our solution to the overflow/underflow problem is roughly similar to Sachnev et al.'s

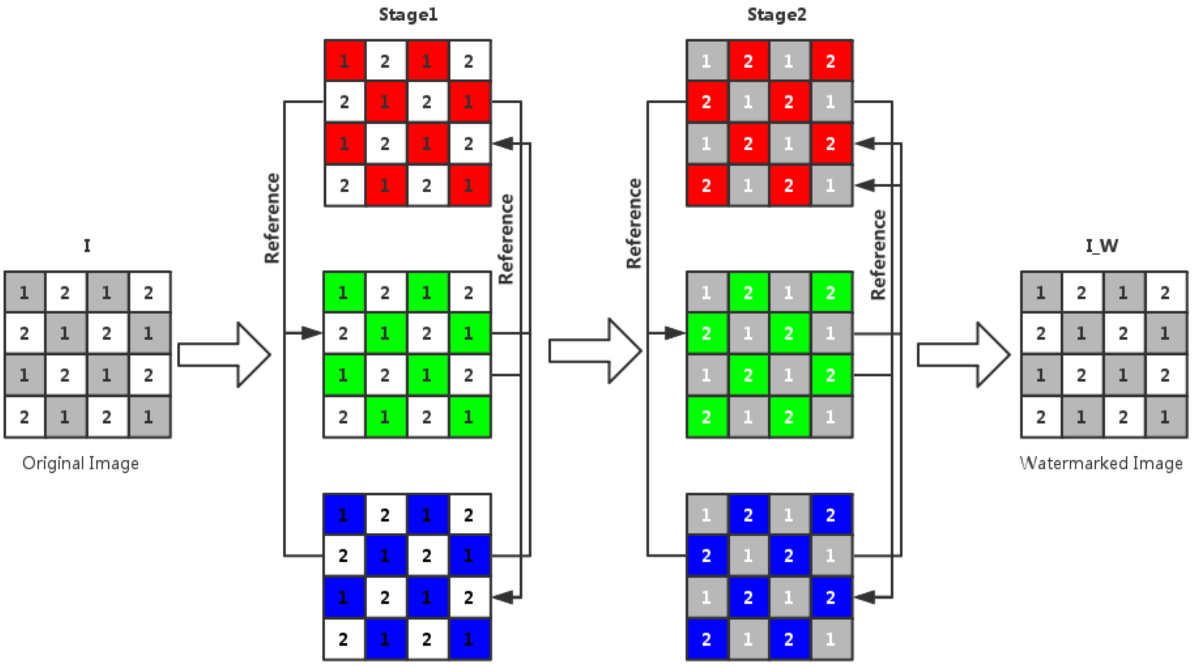

FIGURE 4. The process of data hiding for three channels

one [22]. It defines a location map where the pixels that might cause overflow/underflow are modified and marked with 1, while the others are kept unchanged and marked with 0. The location map will be appended after the secret message as a part of payload after loss-less compressed. Also, for the blind extraction, some auxiliary information (32 bits) should be recorded including embedding threshold t (8 bits), payload partition for current channel EC (16 bits) and the length of location map L (8 bits).

3.1. **Data hiding algorithm.** During the embedding process, all the pixels (or samples in one channel) are classified into two sets, differently indicated by white and gray. The input data is embedded into these two sets with two stages, whose embedding process is quite similar. The proposed embedding process for stage 1 is stated as follows:

Step 1: Collect the pixels to be marked in this stage into a sequence $(p_1, p_2, ..., p_n)$. Taking other channels as reference, compute the value C associated with each pixel by means of (7-9) and sort the pixels according to their corresponding characteristic.

Step 2: Predict the pixels in each sequence. Use the rhombus prediction (1) and (6) to generate the prediction-error histogram. Partition half the payload into three parts utilizing the dynamic payload partition, then perform PEE-based reversible data hiding described in (2-4), and construct the location map at the same time.

Step 3: Detect the rest sorted sequence, record the pixels that might cause overflow/underflow into location map, and record its length L.

Step 4: Record the LSBs of the first 32 pixels in the first stage in the current channel, then replace these bits by the auxiliary information mentioned above, and embed the location map and the recorded bits into the rest sequence using PEE, (2-4).

3.2. **Data extraction algorithm.** The data extraction is processed in inverse order, i.e. we first recover stage 2 and the stage 1. The detail procedure of data extraction and recovery is described as follows:

Step 1: Collect the pixels to be marked in this stage into a sequence $(p_1, p_2, ..., p_n)$. Sort the pixels according to their corresponding value C.

Step 2: Read the first 32 pixels LSBs as the auxiliary information in each channel. Obtain the corresponding parameters t, EC and L.

Step 3: Predict the blank pixels using rhombus prediction and use the prediction errors to extract hiding message. Extract the data in $(p_{EC+L+1}, p_{EC+L+2}, , p_{EC+L+32})$ and use the data to replace the first 32 pixels LSBs. Extract the data in $(p_{EC+1}, p_{EC+2}, , p_{EC+L})$ and use the data to construct location maps. Recover the pixels at the same time.

Step 4: Extract the embedded message in $(p_1, p_2, , p_{EC})$ utilizing the parameters t, EC and the constructed location map. Meanwhile, recover the pixels as Step 3. Thus, the single stage of the image is recovered.

4. **Experimental results.** In this section, we tested the performance of the proposed method and compared it with state-of-art methods via both embedding capacityCdistortion curves and average running time. Here, two algorithms are specially designed for color image [29, 30], and two are state-of-the-art PEE-based algorithms designed for the gray-scale images [17, 22]. For Hong et al.'s, Sachnev et al.'s and Li et al.s algorithms, the data is equally divided and embedded into the each channel. In our experiments, we focused on the performance of distortion control and time efficiency, and mainly compared the proposed method with method for color image [29, 30].

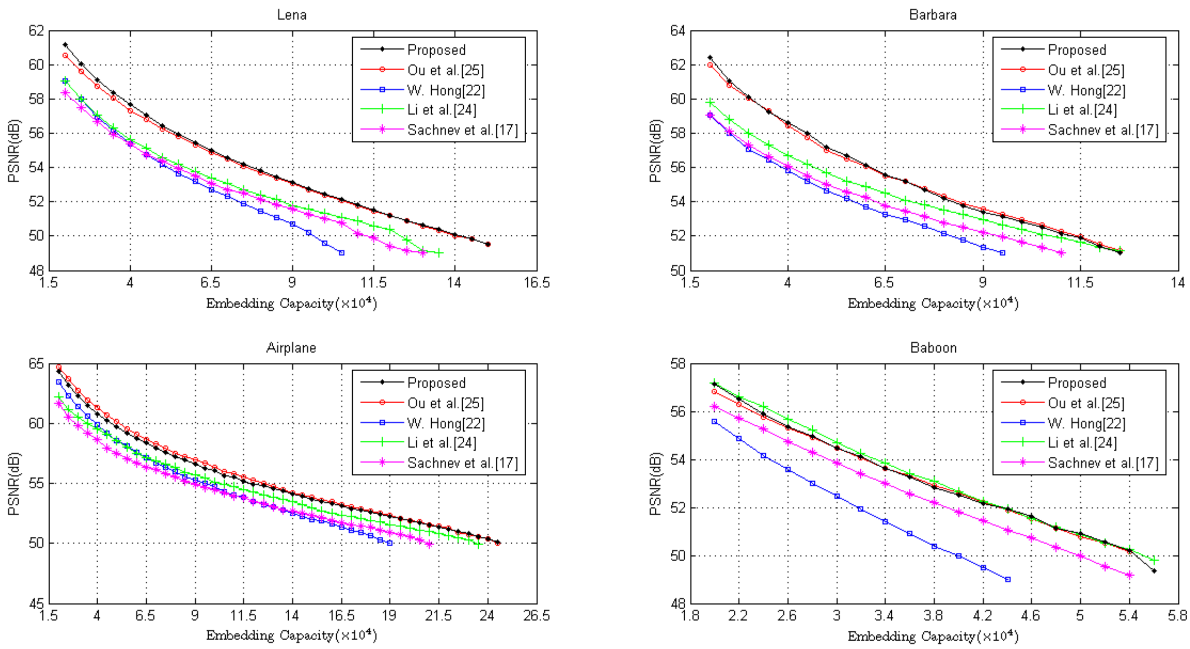

FIGURE 5. Performance comparison between our method and four methods of Ou et al. [30], Hong et al. [27], Li et al. [29] and Sachnev et al. [22].

Fig. 5 shows the performance comparison on four standard 512×512 sized color images, Lena, Baboon, Airplane and Barbara, considering only the case of $t = 1$ in order to control variables. It can be seen from Fig. 5 and Table. 1 that our proposed RDH algorithm performances obviously better than the existing state-of-the-art gray image algorithms [17, 22] in terms of embedding distortion and capacity, as the proposed method used the correlation between the channels better and make full use of embedding capacity under the fixed threshold. And the proposed method is not inferior to color image algorithms [29,30]. Apart from test image like Baboon whose capacity difference between channels which is not obvious, the proposed method got significant improvement on distortion control comparing to Li et al. [29]. Although the proposed method used approximate solution in place of the global optimal solution of payload partition combination, the embedding performance is not inferior to Ou et al. [30]. Moreover, as the proposed method improved sorting strategy utilizing both local complexities in current channel and the correlation cross channel, the proposed method might get better performance than Ou et al. [30] in some capacity regions, e.g. lower capacity region for Lena and Baboon.

Table 1. Performance comparison on $four$ standard images for a capacity of 40,000 bits

Images	Ou. [30]	Hong. [27]	Li. [29]	Sachnev. [22]	Proposed
Lena	57.33	55.35	55.64	55.31	57.66
Barbara	58.45	55.8	56.68	56.06	58.64
Airplane	61.3	59.85	59.65	58.62	60.82
Baboon	52.58	49.96	52.63	51.8	52.5
Average	57.42	55.24	56.15	55.45	57.41

Furthermore, in order to prove the high time efficiency of proposed method. We also give the average running time of once embedding on the four standard images. All the experiments are implemented by Matlab 7.0.0, and tested on a Lenovo personal PC with 2.53 GHz CPU and 2GB memory.

Table 2. Performance of running time comparison on four standard images

Images	Ou. [30]	Li. [29]	Sachnev. [22]	Proposed
Lena	37.9856	29.7709	7.8413	18.2241
Barbara	35.7324	27.9619	6.9108	17.8205
Airplane	40.9859	33.7629	8.7548	19.4869
Baboon	39.4306	32.4280	6.6371	18.7496
Average	38.5336	30.9809	7.5360	18.5703

As it analyzed above, the computational complexity of payload partition proposed by Ou et al is $O(R_{max} \times G_{max} \times B_{max})$, which is decided by the size of the combination space. By utilizing the dynamic payload partition, there is no need to traverse over all the combinations of (EC_R, EC_G, EC_B) satisfying the capacity requirement, and the time efficiency has been significantly improved. As the greedy algorithm is used in the dynamic payload partition, the payload combination will be constructed without traversing over all combinations to choose the optimal result and better computational complexity of payload partition will be obtained. During the payload partition process, all the prediction errors will be processed only once, so the computational complexity is $O(R_{max} + G_{max} + B_{max})$. From table 2 it obviously that the time efficiency of proposed method is highly improved compared with other color image algorithms. By utilizing dynamic payload partition the running speed of proposed method is over 200% of Ou et als method which uses global payload partition. Overall, the proposed method achieves outstanding performance comprehensively considering distortion control and time efficiency.

5. **Conclusions.** In this paper, a novel RDH method for color images is proposed based on dynamic payload partition and cross-channel correlation. Utilizing the correlation of prediction-errors across the channels, a new sorting strategy for selection of data hiding

position is proposed. On this basis, extending existed channel-dependent payload partition schemes, the proposed method used greedy algorithm to get approximate optimal parameter instead of exhaustive search and improved the time efficiency extremely. Experimental results on standard images demonstrate that the proposed method achieves better performance comprehensively considering distortion control and time efficiency than prior state-of-the-art methods.

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