LETTER

Improved Histogram Shifting Technique for Low Payload Embedding by Using a Rate-Distortion Model and Optimal Side Information Selection

Junxiang WANG[†,††], **Jiangqun NI**[†a)], **Dong ZHANG**[†], *Nonmembers*, *and* **Hao LUO**[†††], *Member*

SUMMARY In the letter, we propose an improved histogram shifting (HS) based reversible data hiding scheme for small payload embedding. Conventional HS based schemes are not suitable for low capacity embedding with relatively large distortion due to the inflexible side information selection. From an analysis of the whole HS process, we develop a rate-distortion model and provide an optimal adaptive searching approach for side information selection according to the given payload. Experiments demonstrate the superior performance of the proposed scheme in terms of performance curve for low payload embedding.

key words: *histogram shifting, reversible data hiding, rate-distortion model, optimal side information selection*

1. Introduction

As a special branch of data hiding schemes, reversible data hiding techniques enable the decoder to not only extract the secret data as traditional schemes, but also perfectly reconstruct the original cover image without any distortion. Therefore, it is generally utilized in some specific scenarios, such as military, medical and legal applications.

As two main categories in reversible data hiding schemes, difference expansion (DE) [1]–[4] and histogram shifting (HS) [5]–[8] techniques have been greatly developed. Tian [1] first proposed the DE based scheme by expanding LSBs of pixel differences to hide secret data. To increase embedding capacity and enhance the stego-image quality, small DWT coefficients in [2] and precious rhombus prediction errors in [3] were employed as pixel differences to implement expansion and hide messages, respectively. In addition, to obtain desirable stego-image quality in low payload situation, the pixel differences could be sorted and those with less distortion were determined to be expanded and used to hide data. To the best of our knowledge, Sachnev *et al.* [3] has almost achieved the best rate-distortion performance, especially for for low payloads, due to the precious rhombus prediction and sorting technique. The adaptive selection scheme based on the sorting technique was also employed in [4] for multiple expansion and achieves a larger capacity.

The other category, the first histogram shifting (HS) technique, was proposed by Ni *et al.* [5]. It selects the inflexible highest frequency bin and closest zero frequency bin as peak and zero bins in histogram and then shifted the bins between the selected peak and zero bins towards zero bin by one unit for reversible data embedding. Since the scheme was implemented in the pixel domain, the performance is limited. Later, Fallahpour *et al.* [6] divided the cover image into blocks and then performed HS on each block to enhance the embedding capacity. To sharpen the histogram and further increase capacity, the HS technique was extended to prediction errors in [7] and [8]. However, these approaches for peak and zero bins selection were inflexible, such as Tai *et al.* [8] chose a certain bin located in the middle of a histogram and outer zero frequency bin as peak and zero bins. Therefore, the performances of those schemes, especially in the case of low payload embedding, were scarified. Actually, for some medical applications, secret data to be hidden in a medical image may be the basic information of a patient and the size is only several bits. Meanwhile, it is expected that most symptoms can be preliminarily judged via the received high-quality stego-image without performing the restoration all the time.

In this letter, we develop a rate-distortion model based on the HS process and then propose an optimal side information selection approach according to the given low payload. Experimental results show the superiority of our proposed scheme.

The remainder of the paper is organized as follows. The proposed algorithm is introduced in Sect. 2. Experimental results and conclusion are given in Sects. 3 and 4, respectively.

2. The Proposed Method

2.1 Conventional Histogram Shifting Schemes in Prediction-error Domain

Conventional histogram shifting schemes in prediction-error domain could be generally performed in three stages, i.e. prediction errors computation, data embedding by using histogram shifting and stego-pixels construction. Meanwhile various predictors will lead to different performances.

Denote a grayscale pixel and the corresponding predic-

Manuscript received March 2, 2012.

Manuscript revised June 5, 2012.

[†]The authors are with Sun Yat-Sen University, Guangdong, China.

[††]The author is with Jingdezhen Ceramic Institute, Jiangxi, China.

[†††]The author is with Zhejiang University, Zhejiang, China.

a) E-mail: issjqni@mail.sysu.edu.cn

DOI: 10.1587/transinf.E95.D.2552

	$P(i\text{-}1,j)$	
$P(i,j\text{-}1)$	$P(i,j)$	$P(i,j\text{+}1)$
	$P(i\text{+}1,j)$	

Fig. 1 The sketch of prediction.

tion value located in the i-th row and j-th column as $P(i, j)$ and $\tilde{P}(i, j)$, respectively. As shown in Fig. 1, the prediction value for one pixel in [7] and [3] can be evaluated by (1) and (2), respectively.

$$\tilde{P}(i, j) = P(i, j + 1) \tag{1}$$

$$\tilde{P}(i, j) = round[(P(i - 1, j) + P(i + 1, j) + P(i, j - 1) + P(i, j + 1))/4] \tag{2}$$

where the function $round(\bullet)$ returns the nearest integer of the input.

Thus, the prediction error is computed as

$$PE(i, j) = P(i, j) - \tilde{P}(i, j) \tag{3}$$

Based on the prediction errors $PE = \{PE(i, j)\}$, which are processed in the raster scan order, histogram shifting scheme (HS) is employed to hide secret data and generate the stego-prediction errors $PE' = \{PE'(i, j)\}$. For the given peak/zero frequency bin pair Pb and Zb, called side information, HS first shifts the histogram bins between Pb and Zb towards the Zb direction to create a vacant position near Pb, then scan each prediction error and embed 1-bit message w when Pb is encountered. Assume $Pb < Zb$, the HS process can be expressed by

$$PE'(i, j) = \begin{cases} PE(i, j)+1, & if\ PE(i, j) \in U(Pb, Zb) \\ PE(i, j)+1, & if\ PE(i, j) = Pb\ and\ w = '1'; \\ PE(i, j), & otherwise \end{cases} \tag{4}$$

where $U(Pb, Zb)$ denotes the open set between Pb and Zb.

Instead of the conventional approaches, we take advantage of a rate-distortion model to optimally determine the peak/zero bin pair in HS embedding, as will be introduced in following subsections.

To construct the stego-pixel $P'(i, j)$, we have

$$P'(i, j) = \tilde{P}(i, j) + PE'(i, j) \tag{5}$$

The date extraction and stego-image restoration could be implemented in the reverse order as the embedding process.

2.2 The Rate-Distortion Model

In this subsection, we analyze the HS process and develop a rate-distortion model to direct the optimal side information selection.

For HS based embedding with Pb and Zb as the pair of peak and zero bins, the embedding capacity (rate) is calculated as

$$Capacity = h(Pb) \tag{6}$$

where $h(\bullet)$ denotes the frequency function in histogram.

The distortion between original and stego pixels due to HS based embedding can be expressed as

$$D = P'(i, j) - P(i, j) = PE'(i, j) - PE(i, j) \tag{7}$$

The distortion D in (7) can be further decomposed into two parts. One is the distortion caused by shifting the histogram bins between Pb and Zb towards the Zb direction by 1, which is defined as the shifting distortion D_s and calculated by

$$D_s = \sum_{m \in U(Pb,Zb)} h(m) \times (\Delta m)^2 = \sum_{m \in U(Pb,Zb)} h(m), (\Delta m = 1) \tag{8}$$

The other part of the distortion is introduced when secret data $w = 1$ and Pb changes to its neighboring vacant bin, which is known as the embedding distortion D_e. For a binary data array of length L, if we assume the '0' and '1' in the array are equally distributed, the D_e can be estimated as

$$D_e = \sum_{(n=Pb)\&(w=1)} (\Delta n)^2 = \frac{1}{2} \times L, (\Delta n = 1) \tag{9}$$

For the target capacity C, the HS based reversible embedding can be formulated as the following capacity constrained optimization problem

$$\begin{cases} \underset{Pb,Zb}{Min}\ D_s + D_e = \underset{Pb,Zb}{Min} \sum_{m \in U(Pb,Zb)} h(m) + \frac{1}{2} \times C \\ s.t. \quad h(Pb) \geq C \end{cases} \tag{10}$$

2.3 Optimal Side Information Selection

In this subsection, our aim is to choose the optimal peak and zero bins pair to achieve the minimum distortion $(D_s + D_e)$ under the constraint condition $h(Pb) \geq C$.

When the secret data is given, the embedding capacity (rate) and embedding distortion D_e are determined. Thus we focus on minimizing D_s. According to (8), for a given histogram, the shifting distortion D_s greatly depends on the length of the interval $U = (Pb, Zb)$. Therefore, we propose a "zero-bin first" searching method to rapidly find the optimal Pb and Zb such that the length of interval $U = (P, Z)$ is as small as possible.

Considering the fact that the histogram of the prediction errors almost follow the Laplace distribution with mean zero and the peak bins are usually located within the center area of the histogram, the selection for optimal peak and zero bins can be performed according to the following two rules.

Rule 1: Zero bin Zb should be firstly searched from value zero towards positive and negative infinity to ensure that the achieved Zb is close to the peak bin Pb with high possibility.

Rule 2: Based on the chosen zero bin Zb, the peak bin Pb could be researched in the opposite direction towards the centre area until the constraint condition $h(Pb) \geq C$ is satisfied.

Obviously, Rules 1 and 2 ensure our scheme achieve the small distance between Pb and Zb as possible. It is noted that above-mentioned two rules is designed for the predictive errors based schemes with the Laplace distribution instead of the schemes in the pixels domain. Since almost recent similar schemes are generally based on the predictive errors to improve the performance, our schemes can be widely used.

2.4 Embedding and Extracting Processes

Incorporating a high-performance embedding framework proposed in [8], we develop an optimal side information selecion approach by using flexible peak and zero bins for HS process, and describe as follows.

1) Generate prediction errors via (3).

2) Select optimal peak/zero bins as shown in Fig. 2:

   2.1) Scan the histogram from value zero to positive and negative infinity as shown and choose the first encountered zero frequency bins in positive and negative axis as zero bins, respectively, which are denoted as Zb_r and Zb_l.

   2.2) Search two highest frequency bins, denoted as Hb_r and Hb_l, in the intervals $[0, Zb\_r)$ and $(Zb\_l, 0)$ respectively. If embedding capacity $C \geq h(Hb\_r) + h(Hb\_l)$, it goes beyond the scope of low payload embedding in our paper and is not under the consideration of optimal side information selection. Thus we directly let Hb_b and Hb_l be peak bins, designed as $Pb\_r = Hb\_r$ and $Pb\_l = Hb\_l$, respectively. Otherwise, go to step 2.3) to search the optimal peak bins corresponding to Zb_r and Zb_l.

   2.3) Search one or two peak bins in three paths as follows. Then we compare corresponding distortions, denoted as D_1, D_2 and D_3, and determine the optimal peak bins associated with the minimum distortion for HS process.

   Path 1: 'Positive axis-first search'. One peak bin selection in the positive axis: we first search a peak bin in positive axis Pb_r from Zb_r to value zero step by step until Hb_r is encountered or the constraint condition $h(Pb\_r) \geq C$ is satisfied. If $h(Pb\_r) \geq C$ is met, the current bin is considered as the optimal peak bin Pb_r. Therefore, only one pair of peak and zero bins is sufficient and $D\_1 = \sum_{m \in U(Pb\_r,\, Zb\_r)} h(m)$. In the case, maybe several bins in $[0, Zb\_r)$ meet the constraint condition $h(Pb\_r) \geq C$. Our search path ensures the bin closest to zero bin Zb_r is selected as Pb_r to reduce the distortion D_s. Otherwise, if $h(Pb\_r) < C$, another peak bin in the negative axis should be selected as supplementary: let $Pb\_r = Hb\_r$ and supply the similar search in negative axis to determine another peak bin Pb_l under the constraint condition $h(Pb\_r) + h(Pb\_l) \geq C$. Thus $D\_1 = \sum_{m \in U(Pb\_r,\, Zb\_r)} h(m) + \sum_{n \in U(Zb\_l,\, Pb\_l)} h(n)$.

   Path 2: 'Negative axis-first search': The search path is similar to Path 1 and the only dissimilarity is taking negative axis for the first search path and positive axis as supplement. Thus, D_2 can be computed by $\sum_{m \in U(Zb\_l,\, Pb\_l)} h(m)$ or $\sum_{m \in U(Pb\_r,\, Zb\_r)} h(m) + \sum_{n \in U(Zb\_l,\, Pb\_l)} h(n)$.

   Path 3: 'Both sides synchronous search': we synchronously select two optimal peak bins, denoted as Pb_r and Pb_l, on both sides from Zb_r and Zb_l towards zero value step by step until the constraint condition $h(Pb\_r) + h(Pb\_l) \geq C$ is met. Finally $D\_3 = \sum_{m \in U(Pb\_r,\, Zb\_r)} h(m) + \sum_{n \in U(Zb\_l,\, Pb\_l)} h(n)$.

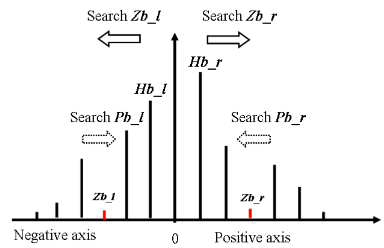


Fig. 2 The illustration of optimal peak and zero bins selection.

3) Perform histogram shifting and embed secret data via (4).

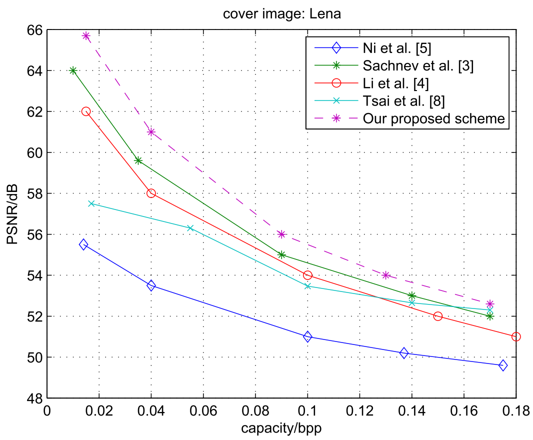
4) Construct the stego-pixels via (5) in the raster scan order and build the stego-image.

Based on the given side information, the extraction could be implemented in the reverse order as embedding process.

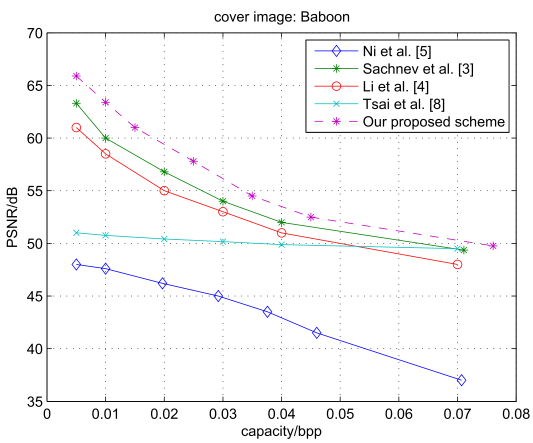
3. Experimental Results

To evaluate the proposed scheme, we test three 512×512×8-bit gray images with different texture characteristics, i.e., Lena, Baboon, F16. By comparing the proposed scheme with some recently high-performance reversible data hiding methods, such as two DE based methods in prediction errors (Sachnev *et al.* [3] and Li *et al.* [4]), and the HS based method proposed by Tai *et al.* [8], for low payload application, the superiority of our scheme is verified.

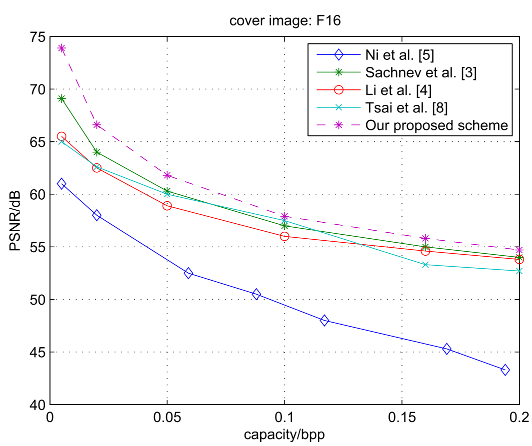
In our implementation, we take advantage of rhombus prediction via (2) to generate prediction errors. As shown in Fig. 3, our scheme achieves the best performance curves at the rate between 0.005 bpp and 0.2 bpp. Compared with DE based schemes [3] and [4], although small prediction errors



(a) Lena



(b) Baboon



(c) F16

Fig. 3 Performance comparison between the proposed scheme and other related schemes in the case of low payload embedding.

were determined to hide secret data by using sorting technique for small capacity embedding, the distortion caused by data embedding via $PE' = 2PE + w$ in DE method is generally not less than that caused by $PE' = PE + w$ in HS based scheme, which shows the advantage of our HS based algorithm. Moreover, since the sorting technique in [3] was performed according to variances computed by neighboring pixels, the actual prediction errors with small value may be not accurately estimated and chosen in some high-texture images. Thus the performance is scarified. In addition, to fairly evaluate the effect of side information selection approaches, the scheme [8] is also applied on rhombus prediction errors. As shown in Fig. 3, the superiority is obvious owing to our optimal side information selection based on the given secret data. Due to the inflexible use of highest frequency bin as peak bin in [8], the shifting distortion D_s is much large versus the embedding distortion D_e. Our optimal side information approach could decrease D_s as possible and only choose the appropriate peak bins to hide secret data. Thus the stego-image quality is greatly improved.

4. Conclusion

In this letter, we proposed an efficient optimal side information selection approach for histogram shifting scheme in the case of low payload embedding. According to the developed rate-distortion model, a rapid optimal side information search path is provided to reduce the shifting distortion as much as possible and achieve high performance. Experiments demonstrated the superiority of our scheme.

Acknowledgments

This work is supported by National Natural Science Foundation of China (No. 60970145 and No. 61100170) and Education Department Science and Technology Project of Jiangxi Province (No. GJJ12512).

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