Reversible Data Embedding using Quad Optimal Transfer Matrix

N. Sateesh
PG scholar, ECE Department,
Sreenivasa Institute of Technology &
Management Studies,
Chittoor-517 127, A.P, India

M. Nand Kumar
Assistant professor, ECE Department,
Sreenivasa Institute of Technology &
Management Studies,
Chittoor-517 127, A.P, India

***Abstract-* In reversible information concealing methods, the values of host information are altered as indicated by some specific standards the first have substance might be splendidly restored the exact data after performing the extraction of the concealed information from recipient side. In this paper, we obtained an number of pixels estimation and dividing the pixels as black and white and an ideal principle of worth alteration using a payload-contortion paradigm was found by utilizing the iterative system, and a handy reversible information concealing plan is proposed. The mystery information, and the assistant data utilized for substance recuperation, is conveyed the contrasts of first pixel-qualities and then comparing qualities evaluated from neighboring pixels. Then, estimated slips are altered as per ideal quality exchange standard. Additionally, the host picture is partitioned into various subsets of pixels and an assistant data of subsets are dependably embedded into the estimated blunders in the following subset. A beneficiary will effectively separate installed mystery information and recuperate an original substance in subsets by a backwards request. Along these lines, a great reversible information concealing execution is attained.**

***Keywords*— Information hiding, pixel estimation, optimal value transfer.**

I INTRODUCTION

Hiding the data system expects to implant various mystery data into a bearer motion by changing the irrelevant segments for clandestine correspondence. By and large cases, the information concealing operation will bring about bending in the host indicator. Be that as it may, such contortions, regardless of how little data, unsuitable to a few other applications like Army or therapeutic pictures. In such situations insert some extra mystery information in a reversible way by this the first substance might be consummately extracted and restored as concealed information.

Various reversible information concealing procedures are proposed, and generally characterized to three sorts. They are compression without any data lose based systems, difference and expansion (DE) methods, and modification of the histogram (MH) techniques. These lossless techniques compose utilization of measurable excess of host data with a specific end goal to make an extra space to suit extra mystery information. In RS technique [1], for instance, a customary solitary position is characterized by every one gathering the pixels as indicated by an operation of flipping with a separation capacity. An aggregate of this method is losslessly packed for given gap to information covering up. Then again, the minimum huge values of the digits to pixel in an L-ary framework [2] or by using the LSB of coefficients of the DCT in a picture [3] can likewise be utilized for giving obliged information. In the information reversing concealing strategies, an extra place can just be made accessible to oblige mystery information the length of the chosen point be compressible.

In difference and expansion strategy [4], contrasts closer to nearby pixels will be multiplied then we get another LSB plane not having any initially created data. The secrete information collectively with a packed area guide inferred from pixel identical, yet not the information of host is insert to a created LSB plane. The packing speed of an area guide will be more, and very nearly every pair of pixel can convey 1 bit, and DE calculation will install the reasonably substantial measure of mystery information to the host picture. Moreover, different strategies have been acquainted into DE calculation with enhance its execution, including summed up whole number change [5], [6], expectation of the pixel value instrument [7], moving of the histogram process [8], forecast of area map[9], rearrangements of area guide [10], [11], and change of compressibility of area guide [12].

Hiding data will likewise utilize histogram change system for acknowledge information hiding. Because of the fact that the first have might be splendidly recouped after data extraction, an information hider dependably plans to bring down the mutilation created by information concealing or to augment the installed payload with a given twisting level, at the end of the day, to attain a decent "payload-bending" execution. In the specified reversible information concealing strategies, the estimations of host information to convey the mystery data, for example, pixel-values, pixel-contrasts and expectation blunders, are constantly altered as per some specific standards. We observe the ideal tenet for a quality adjustment in the payload-twisting foundation in this paper. Through expanding capacity of target utilizing iterative calculation ideal worth exchange framework might be acquired. Moreover, we outline a down to earth reversible information concealing plan, in which the estimation slips of host pixels are utilized to suit the mystery information and their qualities are altered as per the ideal quality exchange grid. Along these lines, a great payload-twisting execution might be attained. instead of dividing host image into two sets can be replaced by four sets and observing results.

The rest of this paper is organized as follows. The optimal value transfer matrix is produced in Section II, and the practical reversible data embedding scheme is described in Section III. Section IV gives the proposed method section V experimental results and Section VI gives concludes the paper

II OPTIMUM TRANSFER OF VALUE

In this we begin the matrix of the transfer value for describing the adjustment of values covered in the information hiding which is reversible to compute optimal transfer of value of matrix and also useful to understand reversible information hiding by using alteration of payload performance. strategies utilizing MH, a specific information accessible to understanding the secret information, for example, contrast of pixels or identification of errors produced as of host picture, then afterward there qualities are modified as indicated by some principles, for example, contrast extension or adjustment of the histogram for performing the retrievable information stowing away. We utilize transfer matrix to form the retrieving information concealing in accessible information. Representing information available for histogram as, $\mathbf{H} = \{. . . , h_{-2}, h_{-1}, h_0, h_1, h_2,. . . \}$,where h_k is the measure of accessible data with a quality k. We denote the existing information belonging to an unique value *i* and a novel value *j* cause by information hiding as $t_{i,j}$, and matrix which is transferred is ended up of $t_{i,j}$ as

$$\boldsymbol{T} = \begin{bmatrix} t_{M_1,M_1} & \cdots & t_{M_1,M_2} \\ \vdots & \ddots & \vdots \\ t_{M_2,M_1} & \cdots & t_{M_2,M_2} \end{bmatrix} \quad (1)$$

Where M1 and M2 are the smallest and highest of the information available. Obviously,

$$\sum_{j=-\propto}^{+\propto} t_{i,j} = h_i \quad (2)$$

And

$$t_{i,j} \geq 0 \quad (3)$$

the novel histogram obtained later modifying the information hiding is

$$h_j^{'} = \sum_{i=M_1}^{M_2} t_{i,j} \quad (4)$$

Indeed MH techniques have relating matrixes which are transferred. For example, in expansion of the difference strategy [4], the distinction of neighbouring pixels is doubled. The secrete bit is implanted as minimum noteworthy bit for the novel distinction value.

$$d^{'} = 2.d + b \quad (5)$$

Where d, b, and d' are unique difference-pixel, the Difference of new value, and a mystery bit. The transfer matrix is

$$\mathbf{T} = \begin{bmatrix} \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & ⋰ \\ \cdots & \frac{h_{-1}}{2} & \frac{h_{-1}}{2} & 0 & 0 & 0 & 0 & \cdots \\ \cdots & 0 & 0 & \frac{h_0}{2} & \frac{h_0}{2} & 0 & 0 & \cdots \\ \cdots & 0 & 0 & 0 & 0 & \frac{h_1}{2} & \frac{h_1}{2} & \cdots \\ ⋰ & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix}. \quad (6)$$

Distinctive modification of the histogram in observing a crest and a null point of an unique histogram, the values among them are moved to the null point by 1, and other points which are good will be moved by 1 to the null .Denote p and *z* as gray values relating the crest and zero points in a histogram. Assume p<z. So, the transfer matrix is

$$\mathbf{T} = \begin{bmatrix} \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & ⋰ \\ \cdots & h_{p-1} & 0 & 0 & 0 & \cdots & 0 & 0 & \cdots \\ \cdots & 0 & \frac{h_p}{2} & \frac{h_p}{2} & 0 & \cdots & 0 & 0 & \cdots \\ \cdots & 0 & 0 & 0 & h_{p+1} & \cdots & 0 & 0 & \cdots \\ \cdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \cdots \\ \cdots & 0 & 0 & 0 & 0 & \cdots & h_{z-1} & 0 & \cdots \\ \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & h_{z+1} & \cdots \\ ⋰ & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix} \quad (7)$$

The distortion caused by data hiding is

$$D = \sum_{i=M_1}^{M_2} \sum_{j=-\propto}^{\propto} [t_{i,j} . d(i,j)] \quad (8)$$

d (i.j) is the distortion energy during the change of the unique value i of an available information to a novel value j. In DE method [4], the difference of the values is changed by correcting the pixels of the two. That means

$$d(i,j) = \begin{cases} \frac{(j-i)^2}{2}, & if\ (j-i) is\ even \\ \frac{[(j-i)^2+1]}{2}, & if (j-i) is\ odd \end{cases} \quad (9)$$

And, in the histogram adjustment scheme in distortion of the energy occurred after varying an unique pixel-value *i* to a novel value of *j* is

$$d(i,j) = \frac{(j-i)^2}{2} \quad (10)$$

Taking the available information with unique value i, the highest information quantity carried is given by,

$$\boldsymbol{t}_i^{(R)} = [\ldots\ t_{i,-1}\ \ t_{i,0}\ \ t_{i,1}\ \ldots\ldots] \quad (11)$$

$$\boldsymbol{t}_i^{(C)} = [\,t_{M_1,j}\ \ t_{M_1,j}\ \ldots\ldots\ldots\ \ t_{M_1,j}\,]^T \quad (12)$$

In addition taking information with novel value j after hiding the information, it is required to retrieve their unique values, the required information is

Where H is entropy function

$$\boldsymbol{E}(\boldsymbol{t}_i^{(R)}) = h_i . H\left(\ldots.. \frac{t_{i,-1}}{h_i}\ \ \frac{t_{i,0}}{h_i}\ \ \frac{t_{i,1}}{h_i} \ldots\ldots\right) \quad (13)$$

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Hence, the information amount is,

$$H\left(\ldots.\frac{t_{i,-1}}{h_i}\quad\frac{t_{i,0}}{h_i}\quad\frac{t_{i,1}}{h_i}\ldots\ldots.\right)$$

$$=\sum_{j=-\infty}^{\infty}\frac{t_{i,j}}{h_i}.log\frac{h_i}{t_{i,j}}\qquad(14)$$

Furthermore, considering the available information with new value j after information hiding. Since we need to recover their original values, the minimal amount of required information is

$$\boldsymbol{E}(\boldsymbol{t}_i^{(C)})=h_j^{'}.H\left(\frac{t_{M_1,j}}{h_j}\quad\frac{t_{M_1+1,j}}{h_j}\ldots\ldots\ldots.\frac{t_{M_2,j}}{h_j}\right)$$

$$=\sum_{i=M_1}^{M_2}t_{i,j}.log\frac{h_j^{'}}{t_{i,j}}\qquad(15)$$

Thus, the information amount of pure payload is

$$P=\sum_{i=M_1}^{M_2}\boldsymbol{E}(\boldsymbol{t}_i^{(R)})-\sum_{j=-\infty}^{\infty}\boldsymbol{E}(\boldsymbol{t}_i^{(C)})\qquad(16)$$

From above equation, an information-hider at all times to get a good payload performance is obtained. Define a Lagrange function

$$L=P-\sum_{i=M_1}^{M_2}(\alpha_i.\sum_{j=-\infty}^{\infty}t_{i,j})-\lambda\sum_{i=M_1}^{M_2}\sum_{j=-\infty}^{\infty}[t_{i,j}.d(i,j)]\qquad(17)$$

When we meet an extreme value of P,

$$\frac{\partial L}{\partial t_{i,j}}=\log\frac{h_i}{h_j^{'}}-\alpha_i-\lambda.d(i,j)=0\qquad(18)$$

The essentials in **T** are non-negative. According to (18), if $t_{i,j}$ and $t_{i,k}$ are positive

$$\frac{\log(\frac{h_j^{'}}{h_k})}{d(i,k)-d(i,j)}=\lambda\qquad(19)$$

By the provision given in (17), we will make use of the following numerical iterative method for calculating the optimal matrix.

1. Initialize

$$\mathbf{T}=\begin{bmatrix}h_{M_1}&0&\cdots&0\\0&h_{M_1+1}&\cdots&0\\\vdots&\vdots&\ddots&\vdots\\0&0&\cdots&h_{M_2}\end{bmatrix},\qquad(20)$$

and D=0, P=0.

2. Compute the novel histogram $\mathbf{H}'$ by (4).
3. Each $t_{i,j}$ and each k , calculate

$$\lambda(i,j,k)=\frac{\log(\frac{h_j^{'}}{h_k})}{d(i,k)-d(i,j)}\qquad(21)$$

By (19), the values of (i,j,k) must be similar in the transfer matrix. So, identifying the leading one among the all calculated λ(i,j,k),we denote there respective i,j and k as i*,j*, and k* . The new transfer matrix is,

$$t_{i^*,j^*}=t_{i^*,j^*}-\Delta\qquad(22)$$

$$t_{i^*,k^*}=t_{i^*,k^*}+\Delta\qquad(23)$$

We reduce the major of λ(i,j,k) for equalizing all of λ(i,j,k).

4. We calculate the level of distortion D and payload P by using (8) and (16). The value of **T** is just the optimal matrix to get payload and the level. 2. Utilizing the above-depicted system, with the increase of pure payload and also increase of distortion level on the other hand the value of (i',j',k') reduces along with using more iterations. In this manner, the optimal matrixes relating to different payloads and the level of distortion level is achieved. In III Section, we use retrieving information by using optimal value matrix is shown.

III REVERSIBLE DATA EMBEDDING SCHEME

In this the hidden information, and also the secondary information used to recover the content was obtained by performing the difference between the novel pixels and

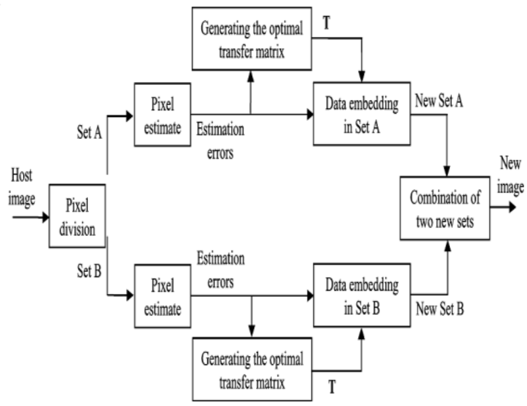

Fig. 1.Procedure for Embedding of data.

We estimate the required values from the near by pixels and we modify the errors identified .the new matrix with the more data hiding is produced. The data implanted is orderly executed in the subsets by making division as two sets and a amount of subsets, the secondary data of a subset is produced and implanted the errors estimated in subsequently subset. In the inverse order, a receiver can effectively extract the embedded secret data and retrieve the original content from the subsets.

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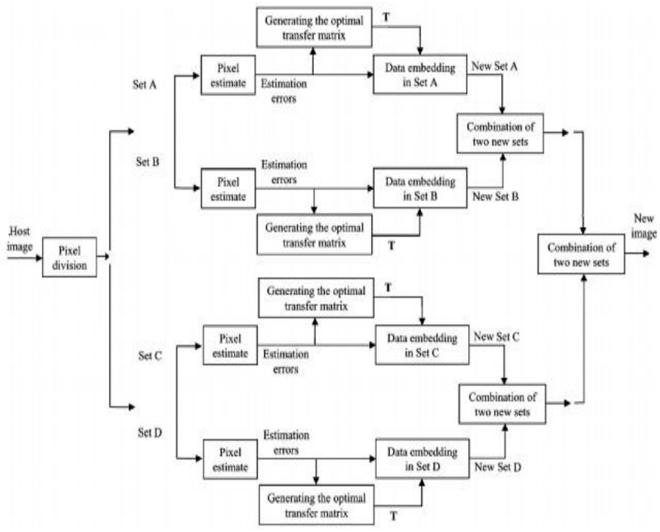

Fig. 2.Procedure for Embedding of data in four sets

We estimate the required values from the near by pixels and we modify the errors identified .the new matrix with the more data hiding is produced. The data implanted is orderly executed in the subsets by making division as four sets and a amount of subsets, the secondary data of a subset is produced and implanted the errors estimated in subsequently subset. In the inverse order, a receiver can effectively extract the embedded secret data and retrieve the original content from the subsets.

A. Embedding of data

The embedding of data procedure is shown in Fig.2. We represent the host pixels as $p_{u,v}$ .in which u and v are the row and column .Now, we divide the pixels as four unique sets which produce the odd (u-v) and even (u+v) pixels. The figure

Looks like a crossword fashion which is like black and white and light black and light white pixels

$$p_{u,v}^{(E)} = w_{-1,0} \cdot p_{u-1,v} + w_{1,0} \cdot p_{u+1,v} + w_{0,-1} \cdot p_{u,v-1} + w_{0,1} \cdot p_{u,v+1} \qquad (24)$$

Where, w-1, 0, w0, 1, w0,-1and w0, 1 are the weights, and the estimation error is

$$e_{u,v} = p_{u,v} - p_{u,v}^{(E)} \qquad (25)$$

That means the pixels in Set A/B and Set C/D are estimated by using the pixels in B/A and D/C. The data embedding procedure is made up of

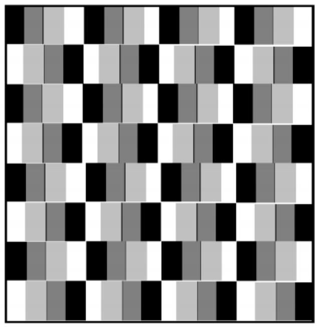

Fig. 3.Division of pixels is in crossword fashion. The white and black and light white and light black pixels belong to Sets A and B and C and D respectively.

Embedding of data for identifying errors in Set A and Set B and Set C and Set D before embedding the data for identifying errors in Set A, we initially identify the finest weights with the LSE,

$$\{w_{-1,0}^{*}, w_{1,0}^{*}, w_{0,-1}^{*}, w_{0,1}^{*}\} = \underset{\{w_{-1,0}, w_{1,0}, w_{0,-1}, w_{0,1}\}}{argmin} \sum_{p_{u,v} \in setA} e_{u,v}^{2} \qquad (26)$$

Then, the actual estimation errors are calculated according to the optimal weights and rounded; see equation (27) at the bottom of the page. Let the histogram of estimation errors be and the number of estimation errors

$$e_{u,v} = \text{round}\left[p_{u,v} - \left(w_{-1,0}^{*} \cdot p_{u-1,v} + w_{1,0}^{*} \cdot p_{u+1,v} + w_{0,-1}^{*} \cdot p_{u,v-1} + w_{0,1}^{*} \cdot p_{u,v+1}\right)\right] \qquad (27)$$

$g_k = \{\ldots\ldots, g_{-2}, g_{-1}, g_0, g_1, g_2, g_3 \ldots\ldots\}$ be, which equals half of the size of host image. Generally speaking, decreases with increasing. Then, find two values and satisfying

$$g_{M2} \geq \frac{N}{4096}, and \quad g_k < \frac{N}{4096} \quad , k < M_1 \qquad (28)$$

and

$$g_{M2} \geq \frac{N}{4096}, and \quad g_k < \frac{N}{4096} \quad , k > M_2 \qquad (29)$$

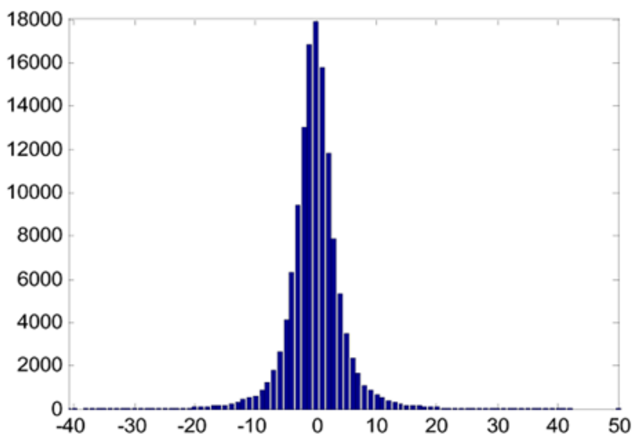

Fig 4. Histogram of estimation errors G set A in Lena

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Discard the trivial parts of the histogram on the left of M1 and M2 on the right of, and calculate a scaled histogram in central are

$$h_{k=}round\left(\frac{g_k}{\frac{N}{2048}}\right),\quad M_1 \leq \mathrm{k} \leq M_2 \qquad (30)$$

Clearly, the scaled histogram on the left of M1 and M2 on the right of must be zeros, therefore will be ignored. For example, when a gray scale image Lena sized 512× 512 was used as the host, the optimal estimation weights for Set A were $w^*_{-1,0}$=0.406, $w^*_{0,1}$=0.408, w^*_{0-1}=0.094 and $w^*_{0,1}$=0.093 The histogram of estimation errors G and the scaled histogram H are shown in Figs. 4 and 5. The purpose of is to filter the trivial parts and to quantize the histogram. The larger number of quantization levels implies more precision of quantized histogram and more required data for representing the quantized histogram. To make a trade off, we use the values 4096 and 2048 here. In fact, other values, such as 5000 and 3000, are also suitable and can provide a similar performance. Note that the histogram has been scaled to avoid the effect of image size, and the optimal transfer matrix will be calculated from the scaled histogram.

Then, employ the iterative steps described in the previous section to obtain an optimal transfer matrix corresponding to a certain pure payload and distortion level from the histogram H. Here, when calculating λ (i,j,k) in i, j, and k must fall into [M1, M2], and d (i,j). To make a trade off between the precision of optimal transfer matrix and the computational complexity, we letΔ=1/8.Actually, the similar value, such as 1/10 or 1/5, can also provide a satisfactory result. We denote the value of λ(i*,j*,k*) in the last iteration as λ_A , and encode the values of the four weights, the scaled histogram H and the number of iterations as a binary sequence C_A . Here, the nonzero elements in the optimal transfer matrix T always locate around the diagonal. Fig. 5 gives an example of optimal transfer matrix generated from the histogram in Fig. 5 by 4.0×10^4 iterations, in which the extreme white represents zero and the extreme black represents the maximal value in T. The computational complexity is proportional to the iteration

number, and the generation of optimal transfer matrix can be finished in several seconds by a personal computer with 2.40 GHzCPUand3.00GBRAM. Divide Set A into a number of subsets with a same size, and perform data embedding in each subset according to the optimal transfer matrix T . For each pixel in a certain subset, denote its original value as and the original estimation error as e . Define a set containing the errors $\bar{e}$ satisfying the following two conditions

$$t_{e,\bar{e}} > 0 \qquad (31)$$

And

$$0 \leq p - \mathrm{e} + \bar{\mathrm{e}} \leq 255 \qquad (32)$$

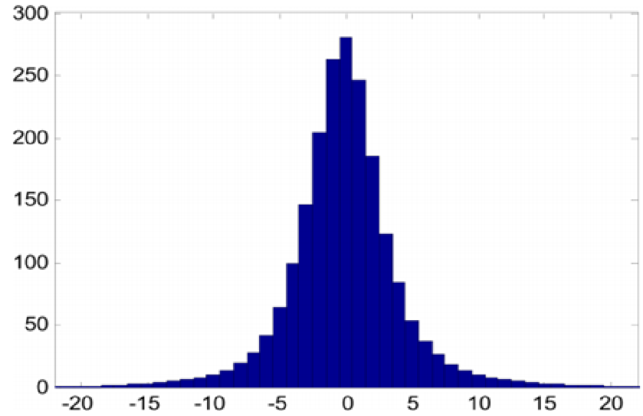


Fig 5 Scaled Histogram H generated from G in fig 4

as available error set (AES). If AES is empty, the original value p will be close to pure white/black and light white/black we do not embed any data into the corresponding estimation error. Furthermore, we modify the pixels from p to 0 or 255 to label them

$$p' = \begin{cases} 0 & ,if\ p \leq 127 \\ 255 & ,if\ p \geq 127 \end{cases} \qquad (33)$$

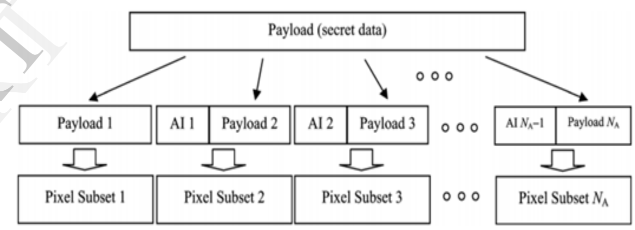


Fig 6 Relationship between the subsets and the embedding data in set A

If AES is not empty, calculate the probability for each $\bar{e}$ in AES according to the optimal transfer matrix T,

$$P_N(\bar{e}) = \frac{t_{e,\bar{e}}}{\sum_{\bar{e}\,\in\,AES} t_{e,\bar{e}}} \qquad (34)$$

Where $\bar{e}$ runs all elements in AES. The probability is just the desirable estimation-error distribution at the pixel. After obtaining the desirable distributions for all pixels with nonempty AES, by employing adaptive arithmetic coding, the data-hider may convert a binary sequence, which will be embedded, into an estimation-error sequence according to the desirable estimation-error distributions. We call the value in the converted sequence as encoded estimation-errors. That means, for a pixel With nonempty AES, the corresponding encoded estimation error obeys the distribution. Denoting the value of an encoded estimation-error with the corresponding original pixel p and original estimation error as e,e' modify the pixel value

$$p' = p + e' - e \qquad (35)$$

The modified value must fall into [0,255] .When finishing the pixel modifications in a subset, we collect some auxiliary information (AI) that will be used for content recovery on receiver side. Here, there are four types of pixels with new values 0 or 255: the first is caused by due to the empty AES, and the second is caused by due to data embedding. We may use one bit to label the type of each saturated pixel. The method assumes the original pixels close to pure white/black and light white/black be rare, so that the number of required labels is small. Record the labels and the original values of the first type of saturated pixels as the first part of auxiliary information. Then, consider the second types of saturated pixels and the unsaturated pixels. Denoting the new estimation error value of a certain pixel as $e^{'}$, calculate the probability

$$P_O(\bar{e}) = \frac{t_{e,\bar{e}}}{\sum_{M_1 \le \bar{e} \le M_2} t_{e,\bar{e}}} \qquad (36)$$

That means the original estimation error e occurs with probability P_O(e). Similarly, by employing arithmetic coding, we convert the sequence of original estimation error into a binary sequence, and regard the binary sequence as the second part of auxiliary information. The distributions are calculated from the optimal transfer matrix, so that a good payload-distortion performance can be achieved by modifying the estimation-errors for data embedding and representing the original estimation-errors for content recovery according to the calculated distributions. Here, we employ the arithmetic coding to convert the payload into new estimation-errors and to convert the original estimation-errors into a binary sequence, i.e., to perform the data embedding and to produce the auxiliary information.

Fig. 6 sketches the relationship between the subsets and the hidden data in Set A. The auxiliary information generated from the k th subset is denoted as AI k . While the data embedded into the first subset are purely the secret data, the data embedded into Subsets 2,3,....N_A consist of the auxiliary information generated from the previous subsets and the secret data, where N_A is the number of the subsets. Since the sizes of the subsets are uniform and we perform the data embedding according to the optimal transfer fashion, the capacities of the subsets, which include the pure payload and the auxiliary information, are approximately same when the size of subset is sufficiently large. That implies the capacity of a subset is always more than the data amount of auxiliary information of the previous subset, leading to an available space for accommodating the secret data.

Denote the histogram of new estimation errors in Set A as , the new scaled histogram

$$h_k^{'} = round\left(\frac{g_k^{'}}{\frac{N}{2048}}\right), \quad M_1 \le \mathrm{k} \le M_2 \qquad (37)$$

And the differences between the new and original scaled histogram

$$d_k = h_k^{'} - h_k \quad M_1 \le \mathrm{k} \le M_2 \qquad (38)$$

Note that AI N_A , the auxiliary information generated from the last subset, and C_A, which is made up of the four weights $w^*_{-1,0}$, $w^*_{0,1}$, $w^*_{0,-1}$, $w^*_{0,1}$, the histogram differences d_k and the iteration number, should be also transmitted to receiver side. Then, we perform data embedding in Set B. At first, we exploit the new pixel-values in Set A to estimate the original pixel-values in Set B by using. After finding four optimal weights, we can also obtain the estimation errors of Set B. Divide Set B into a number of subsets, and denote the histogram of the estimation errors in all subsets except the last one as G. Similarly, discard the trivial parts of the histogram and calculate a scaled central-area histogram H .We also employ the iterative steps described in the previous section to generate an optimal transfer matrix based on the scaled histogram H . Here, the iterative procedure is terminated when

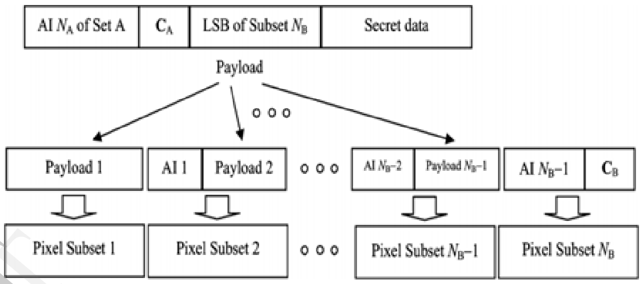


Fig 7 Components of the payload and the relationship between the subsets and the hidden data in set B

the value of λ(i*,j*.k*) is less than λ_A . Then, realize data embedding in each subset except the last one according to the optimal transfer matrix. While the data embedded into the first subset are purely the payload, the data embedded into Subsets 2,3,....N_A consist of the auxiliary information generated from the previous subsets and the payload, where N_B is the number of the subsets. Note that the payload is made up of AI N_A of Set A, C_A , the LSB of the pixels in the last subset of Set B, and the actual secret data to be embedded.

Similarly, collect the values of the four weights, the difference between the new and original histograms of the first N_B-1 subsets, and the number of iterations, and form them into a binary sequence C_B . At last, the auxiliary information generated from Subset N_B-1 and C_B are used to replace the original LSB of pixels in Subset . Fig. 7 shows the components of the payload and the relationship between the subsets and the hidden data in Set B

B. Data Extraction and Content Recovery

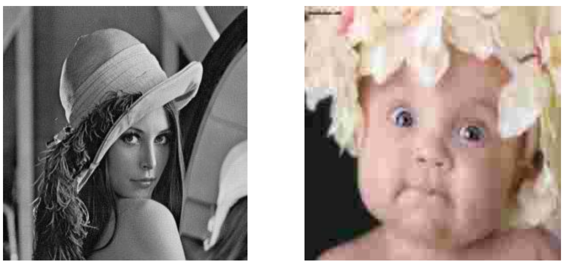
When taking an image that contains an embedded data, firstly the receiver splits the image into Sets A and B and Set C and Set D, and splits Sets A and B and C and D into a number of subsets using the similar manner. Then, extract C_B and AI N_B -1 from the LSB of the last subset in Set B, and decompose C_B as the weight values, the histogram difference of the first N_B -1 subsets and the number of iterations. With the weight values, the receiver can obtain the estimation error $e^{'}$ of each pixel in the first N_B -1 subsets, and with the histogram difference and the iteration number, he can make use of the histogram difference to get back the original scaled histogram **H** and put into practice the iterative procedure to recover the optimal transfer matrix used for data-embedding in the first N_B -1subsets.Then, the receiver recovers the original content and extracts the hidden data in Subset N_B -1 of Set B. Since the first part of AI N_B -1 contains the labels of saturated pixels and the original values of the first type of saturated pixels, the first type of saturated pixels in Subset N_B -1 can be localized and their original values can be recovered.

IV PROPOSED METHOD

The optimal value transfer matrix is produced for maximizing the amount of secret data, i.e., the pure payload, by the iterative procedure described in the previous section. It also stated that the size of auxiliary information would not affect the optimality of the transfer matrix. By pixel division in the original image into two different sets but in enhancement we are using four sets instead of two and number of different subsets, the embedding of the data is orderly performed in the subsets, and then the auxiliary information of a subset is always generated and embedded into the estimation errors in the next subset. Similarly, the receiver could successfully extract the embedded secret data and could recover the original content in the subsets with an inverse order.

V EXPERIMENTAL RESULTS

Two images, Lena, Baby, all sized 512 × 512, shown in Fig. 8 were used as the host images. Both Set A and Set B and Set C and Set D were divided into 32subsets. Since the auxiliary information of a subset is generated after data embedding and embedded into the next subset, we should ensure the capacity of a subset is more than the data amount of auxiliary information of the previous subset. This way, a receiver can successfully extract the embedded secret data and recover the original content in the sub sets with an inverse order. On the other hand, the optimal transfer mechanism implemented in every subset except the last one is used to achieve a good payload-distortion performance. For the last subset, a LSB replacement method is employed to embed the auxiliary information of the second last subset and for content recovery with an inverse order. So, we hope the size of the last subset is small. Considering the two aspects, we make the subset sizes identical and let $N_A = N_B = N_C = N_D = 32$.In this case, the last subset occupies only 1/64 of cover data and almost does not affect the payload-distortion performance. Fig. 9 gives two versions of Lena with different amounts of embedded secret data. Actually, the iteration number for producing the



(a) (b)

Fig 8 Host images (a) Lena (b) Baby

Fig.9.Two versions of Lena containing the embedded secret data: (a) embedding rate 0.8 bpp and PSNR 39.3 dB, (b) embedding rate 1.2 bpp and PSNR 33.5 dB.

optimal transfer matrix or the value of λ(i*,j*.k*) in the last iteration can be used to control the pure payload. The more the iteration number or the smaller the value of λ (i*, j*.k*) in the last iteration, both the pure payload and the distortion level are higher. Since we use the original pixel-values in Set B to estimate the pixels in Set A and use the new pixel-values in Set A to estimate the pixels in Set B, the estimation errors in Set A are closer to zero than those in Set B on the whole . In order to optimize the total payload-distortion performance, we let the iterative procedures in Sets A and B terminate at a same value of λ(i*,j*.k*) . As a consequence, the iteration number and the pure payload of Set A are slightly higher than those of Set B. For Fig. 10(a), the iteration number for generating the optimal value transfer matrix in Set A was 4.0×10^4 , while the number in Set B was 3.7×10^4. In this case, the data amount of pure payload was 1.9×10^5 bits, in other words, the embedding rate, a ratio between the amount of embedded secret data and the number of all host pixels, was 0.8 bits per pixel (bpp). And the value of PSNR caused by data embedding was 39.3 dB. For Fig. 10(b), the iteration numbers in Sets A and B and Set C and D were 8.0×10^4 and 7.2×10^4 , respectively. As a result, 2.7×10^5 secret bits were embedded (1.2 bpp), and PSNR was 33.5 dB. The larger the iteration numbers, a higher pure payload and a lower PSNR value are resulted. If the secret data to be embedded are given, we may assign an iteration number of Set A to ensure 45% of pure payload can be accommodated by the set. Since the pure payload of Set B is slightly lower than that of Set A and Set C 55% of pure payload can be accommodate by the set. .Since the pure payload of Set D is slightly lower than that of Set C when a same terminated λ (i*, j*.k*) is used, the rest pure payload can be successfully carried by Set D.

The previous DE and MH methods can be viewed as the special cases in the model of transfer matrix. Because of the usage of optimal transfer matrix, the proposed scheme could outperform the DE and MH methods in theory. However, the information used to retrieve the optimal transfer matrix at receiver side, which includes the histogram difference, the weights and the iteration number, should be also embedded into the host image. This decreases the pure payload and weakens the advantage of the proposed scheme. Figs. 10–13 compare the performance of several reversible data hiding schemes on the four host images. The abscissa and ordinate represent respectively them bedding rate and the value of PSNR caused by data embedding. The figures show a smoother host image can carry more secret data at a given distortion level or has a lower distortion with a given pure payload. It can be also seen the performance of proposed scheme is better than that of other methods when Lena, Plane and Lake were used as the host. With the host image Baboon, the proposed scheme still outperforms three other methods, and the performance curves of proposed scheme and method are close and intersect each other. Since there is more texture content in this image, the accuracy of pixel estimation is worse in comparison with other images, leading to a flatter histogram of estimation error.

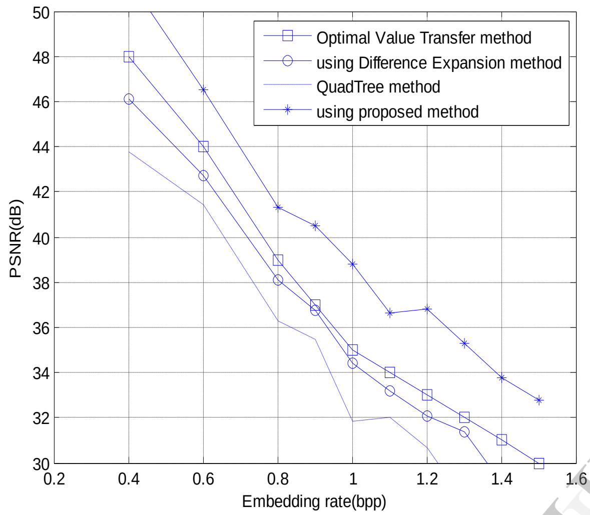


Fig.10 Performance comparison between several reversible data embedding schemes on the host image Lena.

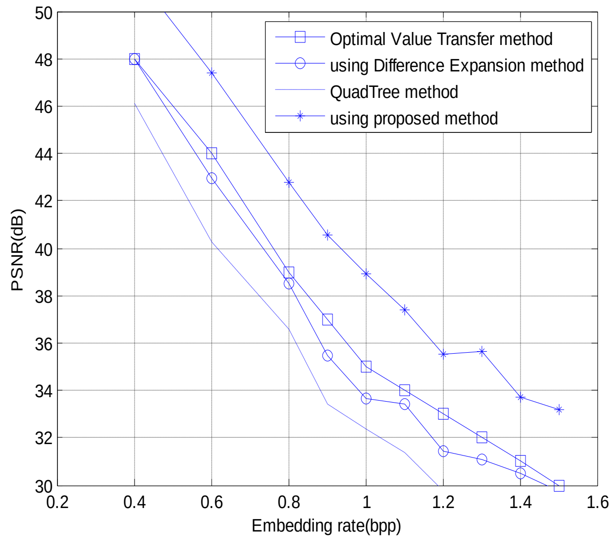


Fig.11 Performance comparison between several reversible data embedding schemes on the host image Baby.

We must use more data to represent the histogram difference, so that the space for accommodating secret data is smaller. However, this affection is insignificant when a large number of secret bits are embedded. So, the performance of proposed scheme is slightly beyond that of method when the embedding rate is high. In short, the proposed scheme outperforms the previous approaches when using smooth images and embedding high payload into rough images.

For each reversible data hiding method, we calculated the average values of embedding rate and PSNR when the same parameters were used in the 50 images. By varying the parameters, the performance curves of the two methods were obtained and shown in Fig. 14. It can be seen that the proposed scheme generally outperforms the method. The proposed scheme consists of four parts: generating four optimal transfer matrixes and data embedding according to the four transfer matrixes. The computational complexities of the four parts are proportional to the iteration number and the pixel number, respectively, and the second part consumes more time than the first part. In each round of the iterations and the data embedding on each pixel, a number of float multiplications and additions should be carried out. For the previous DE and HM methods, the generation of optimal

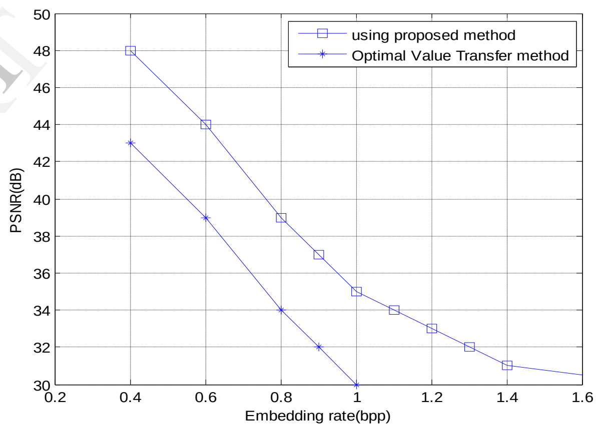


Fig12.Performance comparison between the proposed scheme and the Optimal value transfer method over 50 image

Transfer matrix is needless and only few additions are required for implementing data embedding on each pixel. That means the computational complexity of the proposed scheme is higher than that of the previous methods.

VI CONCLUSION

In order to attain a good payload-distortion performance of reversible data hiding, this work first finds the optimal value transfer matrix by maximizing a target function of pure payload with an iterative procedure, and then proposes a practical reversible data hiding scheme. The contrasts between the first pixel-qualities and the relating qualities assessed from the neighbors are utilized to convey the payload that is made up of the real secret information to be implanted and the auxiliary data for recovery of the original content. As per the transfer matrix of the optimal value, the auxiliary data is created and the estimation blunders are altered. Likewise, the host picture is isolated into various subsets and the auxiliary data of a subset is constantly implanted into the estimation mistakes in the following subset. In this manner one can effectively remove the implanted hidden information and retrieving novel data in to the subsets with a reverse request. For the better host pictures, the future plan essentially performs the past reversible hiding of information in systems. The optimal transfer system proposed in this work is free from the era of accessible cover qualities. On the other hand, the optimal transfer values produce another standard of quality adjustment and could be utilized on different cover qualities. In the event that a more intelligent forecast system is misused to get the expected lapses nearer to zero, a finer execution might be achieved, yet the computation complexity because of the prediction will be higher and the sorts of accessible cover information merits further examination later on.

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ABOUT THE AUTHORS

N.Sateesh received B.Tech degree from JNT University, Anantapur and is pursuing his M.Tech degree from JNT University, Anantapur. He presented 2 technical papers in various national level conferences. His areas of interest are Image processing.

Mr. M.Nanda Kumar working as Assistant professor in the department of ECE in SITAMS, chittoor. He received B.Tech degree from JNT university, Anantapur, M.Tech degree from JNT University, Anantapur. He presented 5 technical papers in various national level conferences and published 4 papers in various journals His areas of interest is wireless communication networksand digital image processing