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Minimum Structural Similarity Distortion for Reversible Data Hiding*

XU Jiajia, ZHANG Weiming, JIANG Ruiqi, YU Nenghai and HU Xiaocheng

(*University of Science and Technology of China, Hefei 230026, China*)

Abstract — Until now, most Reversible data hiding (RDH) techniques have been evaluated by Peak signal-to-noise ratio (PSNR), which based on Mean squared error (MSE). Unfortunately, MSE turns out to be an extremely poor measure when the purpose is to predict perceived signal fidelity or quality. The Structural similarity (SSIM) index has gained widespread popularity as an alternative motivating principle for the design of image quality measures. How to utilize the characterize of SSIM to design RDH algorithm is very critical. We propose an optimal RDH algorithm under structural similarity constraint. We deduce the metric of the structural similarity constraint, and further we prove it does not hold Non-crossing-edges (NCE) property. We construct the rate-distortion function of optimal structural similarity constraint, which is equivalent to minimize the average distortion for a given embedding rate, and then we can obtain the optimal transition probability matrix under the structural similarity constraint. Experiments show that our proposed method can be used to improve the performance of previous RDH schemes evaluated by SSIM.

Key words — Reversible data hiding, Structural similarity, Recursive code construction.

I. Introduction

Reversible data hiding (RDH) [1−4] as a special branch of information hiding, it is not only concerned about the user's embedding data, but also pay attention to the carriers themselves. It requires the carriers to be completely recovered after extracting the embedded message, which has been found to be useful in many fields, such as, medical imagery and legal. A framework of RDH for digital images is illustrated in Fig.1.

In the past few years, reversible hiding has been considerably developed. Scholars have proposed a variety of reversible hiding algorithms for digital images, digital videos, audios, and other carriers[3−5]. Besides, almost Reversible data hiding (RDH) techniques have been evaluated by Peak signal-to-noise ratio (PSNR), Which based on Mean squared error (MSE). Unfortunately, MSE turns out to be an poor measure when the purpose is to predict perceived signal fidelity or quality[6,7]. The reasons lead MSE to be poor measure can be found in paper[6].

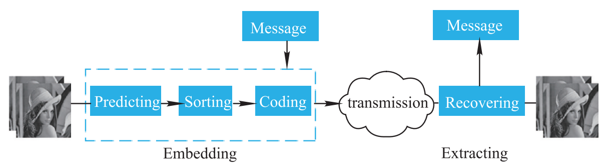

Fig. 1. Framework of RDH embedding/extraction

Recently, the Structural similarity (SSIM) as novel image fidelity or similarity measures, which was originally motivated by the observation that natural image signals are highly structured, has attracted a great deal of attention[6]. The Human visual system (HVS) is the principle philosophy of SSIM approach, which is highly sensitive to the structural distortions and automatically compensates for the nonstructural distortions. The basic ideas of SSIM approach is simulating the HVS functionality, which prove highly effective for measuring the similarity[6]. However, how to utilize the characterize of SSIM to design RDH algorithm? In practice, SSIM is often used as a black box in optimization tasks as merely an adhesive control unit outside the main optimization module. D. Brunet *et al.*[7] construct a series of normalized and generalized (vector-valued) metrics based on the important ingredients of SSIM, and show that such modified measures are valid distance metrics and have many useful properties, such as quasi-convexity, a region of convexity around the minimizer, and distance preservation under orthogonal or unitary transformations.

How to get the optimal for a given embedding rate RDH under structural similarity constraint? Kalker and Willems[8] formulated the RDH as a special rate-

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distortion problem. For independent and identically distributed (i.i.d.) host signals, the upper bound of the payload and a distortion constraint is given by Kalker and Willems [8]. They obtained the rate-distortion function under a given distortion constraint, as follows:

$$\rho_{rev}(\Delta) = \max_{\sum P_X P_{Y|X} D(x,y) \leq \Delta} \{H(Y)\} - H(X) \qquad (1)$$

where X and Y denote the random variables of the host signal and the marked signal respectively. The maximum entropy is over all transition probability matrices $P_{Y|X}(y|x)$ satisfying the distortion constraint $\sum_{x,y} P_X(x)P_{Y|X}(y|x)D(x,y) \leq \Delta$. The distortion metric $D(x,y)$ is usually defined as the square error distortion, $D(x,y) = (x-y)^2$. This problem has been solved in Zhang *et al.* [9−12], Lin *et al.* [13] and Zhang *et al.* [14], who proposed a framework of estimating the Optimal transition probability matrix (OTPM) for general distortion metrics, with which we can calculate OTPM $P_{Y|X}(y|x)$ and $P_{X|Y}(x|y)$. Based on OTPM, we can apply the optimal code constructions to RDH.

In this paper, we propose Minimum structural similarity distortion algorithm (MSSD) for reversible data hiding. Experimental results demonstrate that our proposed method outperforms the previous state-of-arts counterparts significantly in terms of embedding performance evaluated by SSIM.

II. Minimum Structural Similarity Distortion for RDH

1. The fundamental of Stuctural similarity index (SSIM)

In the paper[6], Wang *et al.* has proposed the Structural similarity index measure (SSIM) for image quality assessment, which compares local patterns of pixel intensities that have been normalized for luminance, contrast and structure. Suppose that $x \in \mathbf{R}_+^N$ and $y \in \mathbf{R}_+^N$ are local image signals, which are taken from two images in the same location. The SSIM index separates the task of similarity measurement into three comparisons: luminance, contrast and structure, and the three components are relatively independent.

$$SSIM(x,y) = \frac{2u_x u_y + c_1}{u_x^2 + u_y^2 + c_1} \times \frac{2\sigma_x \sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2} \times \frac{\sigma_{x,y} + c_3}{\sigma_x \sigma_y + c_3} \qquad (2)$$

where $u_x, u_y, \sigma_x, \sigma_y$, and represent, respectively, the mean and variance of x and y. $\sigma_{x,y}$ represent the covariance between x and y. The constants c_1, c_2, c_3 are included to avoid instability when $u_x^2 + u_y^2$, $\sigma_x^2 + \sigma_y^2$ and $\sigma_x \sigma_y$ are very close to zero, respectively. Then, we combine the three comparisons of luminance, contrast and structure, and get the SSIM index function.

The SSIM index is computed locally within a sliding window that moves pixel-by-pixel across the image. The boundedness of SSIM is $1 \geq |SSIM(x,y)|$. Only if $x = y$, the $SSIM(x,y) = 1$. That is to say, the closer that x and y are to each other, the closer $SSIM(x,y)$ is to 1. Besides SSIM have symmetrical $SSIM(x,y) = SSIM(y,x)$.

2. Minimum structural similarity distortion for RDH

Based on Eq.(1), we should design the corresponding structural similarity constraint in order to approach the upper bound of the payload. Does the $SSIM(x,y)$ is a distortion metric? A metric $D(x,y)$ must satisfy four rules for all $x, y, z \in \mathbf{R}_+^N$. Firstly, nonnegativity $D(x,y) \geq 0$. Secondly, symmetry $D(x,y) = D(x,y)$. Thirdly, identity $D(x,y) = 0$ if and only if $x = y$. The last is triangular inequality: $D(x,y) + D(y,z) \geq D(x,z)$.

Clearly, the SSIM index is not a metric, because $x = y \Rightarrow SSIM(x,y) = 0$ and $SSIM(x,y) + SSIM(y,z) \geq SSIM(x,z)$ is not established. However, what's the metric can be used to characterize the structural similarity constraint? We will find a way to "shape" it to form a metric. Based on Eq.(2), we set $c_3 = c_2/2$, then we can get $SSIM(x,y)$ as follows:

$$SSIM(x,y) = \frac{2u_x u_y + c_1}{u_x^2 + u_y^2 + c_1} \times \frac{2\sigma_{x,y} + c_2}{\sigma_x^2 + \sigma_y^2 + c_2} \qquad (3)$$

Theorem 1 Given $x, y \in \boldsymbol{R}$, $\boldsymbol{R}$ is a normed space. Let (p,q) denote the (p,q) relative metric, where $q \neq 0$. The (p,q) relative distance is a metric in $\boldsymbol{R}^n$ if and only if $0 < q \leq 1$ and $p \geq \max\{1-q, (2-q)/3\}$[15].

$$d_{p,q}(x,y) = \frac{\|x-y\|}{A_p(\|x\|, \|y\|)^q} \qquad (4)$$

The special case that we consider is when $A_p(\|x\|, \|y\|)$ equals a power of the power mean, where $A_p(\|x\|, \|y\|)$ is $((\|x\|^p + \|y\|^p)/2)^{\frac{1}{p}}$, $A_0(\|x\|, \|y\|)$ is $(xy)^{1/2}$, $A_{-\infty}(\|x\|, \|y\|)$ is $\min\{x,y\}$, and $A_\infty(\|x\|, \|y\|)$ is $\max\{x,y\}$. Brunet *et al.*[7] construct a series of normalized and generalized (vector-valued) metrics based on the important ingredients of SSIM, and show that such modified measures are valid distance metrics and have many useful properties. Considering set $q = 1$ and $p = 2$, which leads to

$$\begin{aligned} d_{2,1}(u_x, u_y) &= \sqrt{2} \times \sqrt{\frac{\|u_x - u_y\|^2}{(\|u_x\|^2 + \|u_y\|^2 + c_1)}} \\ &= \sqrt{2} \times \sqrt{(1 - \frac{2u_x u_y + c_1}{u_x^2 + u_y^2 + c_1})} \end{aligned} \qquad (5)$$

$$\begin{aligned} d_{2,1}(x-u_x, y-u_y) &= \sqrt{2} \times \sqrt{\frac{\sigma_x^2 - 2\sigma_{x,y} + +\sigma_y^2}{\sigma_x^2 + \sigma_y^2 + c_2}} \\ &= \sqrt{2} \times \sqrt{1 - \frac{2\sigma_{x,y} + c_2}{\sigma_x^2 + \sigma_y^2 + c_2}} \end{aligned} \qquad (6)$$

Observing Eqs.(3), (5) and (6), it is not difficult to find that the relationship among $SSIM(x,y)$, $d_{2,1}(u_x,u_y)$ and $d_{2,1}(x-u_x,y-u_y)$. which can be writen by $SSIM(x,y)=(1-d_{2,1}(u_x,u_y)^2)(1-d_{2,1}(x-u_x,y-u_y)^2)$.

$$\|d(x,y)\|^2 = 1 - SSIM(x,y) \tag{7}$$

If $u_x = u_y$ and $x-u_x = y-u_y$, then $SSIM(x,y)=1$, so we can have

$$\|d_{2,1}(x,y)\|^2 = \frac{\|x-y\|^2}{(\|x\|^2+\|y\|^2+c)/2} \tag{8}$$

$$\|d(x,y)\|^2 = \frac{\|x-y\|^2}{\|x\|\times\|y\|+c/2} \tag{9}$$

where $c \geq 0$. Because $(\|x\|^2+\|y\|^2+c)/2 \geq \|x\|\times\|y\|+c/2$, so $\|d_{2,1}(x,y)\|^2 \leq \|d(x,y)\|^2$.

However, which should we choose as structural similarity distortion constraint between $\|d_{2,1}(x,y)\|^2$ and $\|d(x,y)\|^2$? Both $\|d_{2,1}(x,y)\|^2$ and $\|d(x,y)\|^2$ have been meet the criteria of nonnegativity, symmetry, identity and triangular inequality. So the $\|d_{2,1}(x,y)\|^2$ and $\|d(x,y)\|^2$ are metric, which can be used to characterize the property of $SSIM(x,y)$. The $\|d_{2,1}(x,y)\|^2$ and $\|d(x,y)\|^2$ hold many mathematical properties such as convexity, quasi-convexity, and generalized convexity, which can be derived from SSIM. Assume that a memoryless source produces the host sequence $\boldsymbol{x}=(x_1,x_2,\cdots,x_N)$ with the identical distribution $P_X(x)$ such that $x\in\{0,1,\cdots,B-1\}$, where $B\geq 1$ is an integer. The message is usually encrypted before being embedded, so we assume that the secret message $\boldsymbol{m}=(m_1,m_2,\cdots)$ is a binary random sequence with $m_i\in\{0,1\}$. Through slightly modifying its elements to produce the marked-sequence $\boldsymbol{y}=(y_1,y_2,\cdots,y_N)$. For instance, let $x_1=100$, and the marked-sequence $y_1=1$, then the $\|d_{2,1}(x,y)\|^2=(100-1)^2/(100^2+1^2)=0.98$, and $\|d(x,y)\|^2=(100-1)^2/(100\times 1)=98.01$. So $\|d(x,y)\|^2$ fits the facts better than $\|d_{2,1}(x,y)\|^2$. Based on the property of $SSIM(x,y)$, we selected $\|d(x,y)\|^2$ as structural similarity distortion constraint.

Given $R=L/n$ is embedding rate. Based on $\rho_{rev}(\Delta)=\text{maximize}\{H(Y)\}-H(X)$, the mathematical model can be equivalent to minimize the average distortion for a given embedding rate R, which is formulated as:

$$\begin{array}{ll}\text{minimize} & \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} P_X(x)P_{Y|X}(y|x)\|d(x,y)\|^2 \\ \text{s.t.} & -\sum_{y=0}^{N-1} P_Y(y)\log_2(P_Y(y)) \geq R-H_X \\ & \sum_{x=0}^{M-1} P_X(x)P_{Y|X}(y|x)=P_Y(y),\forall y \\ & \sum_{y=0}^{N-1} P_{Y|X}(y|x)=1,\forall x \\ & P_{Y|X}(y|x)\geq 0,\forall x,y \\ & \|d(x,y)\|^2=\dfrac{\|x-y\|^2}{\|x\|\times\|y\|+c/2},\forall x,y\end{array} \tag{10}$$

where the $P_{Y|X}(y|x)$ is transition probability matrix, $\|d(x,y)\|^2$ structural similarity distortion measures. $P_X(x)$ is the constant parameters are the source distribution.

In Ref.[11], Zhang *et al*. proved that the Lagrange dual[19] of the above rate distortion problem Eq.(10) is of the following form:

$$\begin{array}{ll}\text{minimize} & \gamma\sum_{j=0}^{N-1} \mathrm{e}^{v_j/\gamma-1}+\sum_{i=0}^{M-1} u_i-\gamma H_Y \\ \text{s.t.} & P_X(i)D(i,j)+u_i+P_X(i)v_j\geq 0,\forall i,j \\ & \gamma\geq 0\end{array} \tag{11}$$

The constant parameters are $P_X(i)$, $D(i,j)$, and H_Y.

The optimal solutions v_j and γ of the dual problem Eq.(11) yield the optimal marked-signal distribution of the primal problem Eq.(10) with the following form:

$$P_Y(j)=\mathrm{e}^{v_j/\gamma-1}, j=0,\cdots,N-1 \tag{12}$$

The optimal objective function value of Eq.(21), *i.e.*, the average distortion D_{av}, is given by:

$$D_{av}=-(\gamma\sum_{j=0}^{N-1}\mathrm{e}^{v_j/\gamma-1}+\sum_{i=0}^{M-1}u_i-\gamma H_Y) \tag{13}$$

Theorem 2 [Non-crossing-edges (NCE)] Given an optimal $P^{\dagger}_{Y|X}$, for any two distinct possible transition events $P^{\dagger}_{Y|X}(y_1|x_1)>0$ and $P^{\dagger}_{Y|X}(y_2|x_2)>0$, if $x_1<x_2$, then $y_1\leq y_2$ holds.

Lin *et al*.[13] has been proved that when the distortion metrics $D(x,y)=(x-y)^2$ or $D(x,y)=|x-y|$, the transition probability matrix $P_{Y|X}(y|x)$ has the Non-crossing-edges (NCE) property. Lin[13] pointed out that, by using the NCE property, the joint distribution of X and Y can be expressed by $P_{X,Y}(x,y)=\max\{0,\min\{P_{CX}(x),P_{CY}(y)\}-\max\{P_{CX}(x-1),P_{CY}(y-1)\}\}$, where $P_{CX}(x)$ and $P_{CY}(y)$ are cumulative probability distributions of X and Y defined by $P_{CX}(x)=\sum_{i=0}^{x}P_X(i), x=0,\cdots,M-1$, and $P_{CY}(y)=\sum_{i=0}^{y}P_Y(i), y=0,\cdots,N-1$. Noted that $P_{CX}(-1)=P_{CY}(-1)=0$ and $P_{CX}(M-1)=P_{CY}(N-1)=1$. Therefore, when satisfying NCE property, the OTPM can also be deduced analytically by the marginal distributions $P_X(x)$ and $P_Y(y)$. However, for some distortion metrics, the NCE property may no longer hold and then OTPM cannot be obtained analytically. Does $\|d(x,y)\|^2=(\|x-y\|^2)/(\|x\|\times\|y\|+c/2)$ meet the criteria of NCE?

In Ref.[13], Lin *et al*. define a function $g(x,y)=-\log_2 P^{\dagger}_Y(y)-\lambda\|d(x,y)\|^2$. If we want to prove the NEC property, only need to prove formula holds $g(x_1,y_1)+g(x_2,y_2)\geq g(x_1,y_2)+g(x_2,y_1)$. That is to say $-\lambda\|d(x_1,y_1)\|^2-\lambda\|d(x_2,y_2)\|^2\geq\lambda\|d(x_1,y_2)\|^2-\lambda\|d(x_2,y_1)\|^2$, and this problem is equivalent to $\|d(x_2,y_1)\|^2+\|d(x_1,y_2)\|^2-\|d(x_2,y_2)\|^2-\|d(x_1,y_1)\|^2\geq 0$. That is to say we need to prove whether the below

Eq.(15) is established.

$$\frac{\|x_2-y_1\|^2}{\|x_2\|\times\|y_1\|+c/2}+\frac{\|x_1-y_2\|^2}{\|x_1\|\times\|y_2\|+c/2}- \quad (14)$$

$$\frac{\|x_1-y_1\|^2}{\|x_1\|\times\|y_1\|+c/2}-\frac{\|x_2-y_2\|^2}{\|x_2\|\times\|y_2\|+c/2}\geq 0 \quad (15)$$

Case 1: when $c=0$ and $x_1<x_2, x_1x_2>0$ $y_1\leq y_2$, and $y_1y_2>0$, the above is equivalent to

$$\frac{x_1x_2(y_2-y_1)(x_2-x_1)+y_1y_2(y_1-y_2)(x_1-x_2)}{x_1x_2y_1y_2}\geq 0 \quad (16)$$

Obviously, the above formula is established.

Case 2: when $c\geq 0$, the above Eq.(15) is not established.

So the $\|d(x,y)\|^2$ does not always meet the criteria of NCE. If the NCE property no longer hold and then the optimal transition probability matrix cannot be obtained analytically.

There is a two-step strategy to estimate the optimal $P_{Y|X}(y|x)$. The first step is using the fast algorithm in Ref.[10] to get the marginal distribution $P_Y(y)$ and the corresponding dual variables. Secondly is solving linear program[12] to finally estimate the optimal transition probability matrix $P_{Y|X}(y|x)$. Based on $P_{Y|X}(y|x)$ and P_X, we can calculate the other OTPM $P_{X|Y}(x|y)$.

3. Recursive code construction (RCC) for RDH

RCC has first proposed by Kalker and Willems[8] and developed by Zhang *et al.*[9,11] for RDH, which divides the host sequence into disjoint blocks and embeds the message by recursively modifying the histogram of each block in a bin by bin manner. We first divide the host sequence x into g disjoint blocks.

We embed the message into each block by an embedding function $Emb()$, such that $(\boldsymbol{M}_{i+1}, y_i) = Emb(\boldsymbol{M}_i, x_i)$, with $i=1,\ldots,g$ and $\boldsymbol{M}_1=\boldsymbol{m}$. In other words, the embedding process in the ith block outputs the message to be embedded into the $(i+1)$th block. The $\boldsymbol{M}_{i+1}$ consists of the the rest message bits and the overhead information, $O(x_i)$, for restoring x_i. In each host block x_i, the embedding function $Emb()$ executes two tasks. One task is to embed some bits of the message and generate the stego-block y_i by decompressing the message sequence according to $P_{Y|X}(y|x)$. The other task is to produce the overhead information $O(x_i)$ for restoring the host block $\boldsymbol{x}_i$ by compressing it according to y_i and $P_{X|Y}(x|y)$. The overhead information will be embedded into the next block x_{i+1} as a part of $\boldsymbol{M}_{i+1}$.

The message extraction and cover reconstruction are processed in a backward manner with an extraction function $Ext()$, such that $(\boldsymbol{M}_i, x_i)=Ext(\boldsymbol{M}_{i+1}, y_i)$, with $i=g,\ldots,1$. In each stego block y_i, the extraction function $Ext()$ also executes two tasks. One task is to decompress the overhead information extracted from y_{i+1} according to $P_{X|Y}(x|y)$ and restore the host block x_i. The other task is to extract the message by compressing y_i according to x_i and $P_{Y|X}(y|x)$.

III. Application, Experiment and Analysis

In Ref.[3], Sachnev propose double-layered embedding method. All pixels are divided into two sets: the shadow pixel set ("Dot") and the blank set ("Five Star") (see Fig.2). In the first round, the shadow set is used for embedding data and blank set for computing predictions, while in the second round, the blank set is used for embedding and shadow set for computing predictions. Since the two layers' embedding processes are similar in nature, we only take the shadow layer for illustration.

Next, the prediction-error is computed by $\boldsymbol{e}=P-\hat{P}$ and $\hat{P}=(p_{i-1,j}+p_{i,j+1}+p_{i+1,j}+p_{i,j-1})/4$. Finally, the prediction-error sequence $\boldsymbol{e}=\{e_1,\cdots,e_N\}$ is derived.

In fact, the size of distortion metrics $\|d(x,y)\|^2$ is related to the size of prediction-error. We define $e_{\min}=\min\{e_1,\cdots,e_N\}$ and $e_{\max}=\max\{e_1,\cdots,e_N\}$, so the prediction-error range form $e_{\min}$ to $e_{\max}$. In experiments, we truncate the prediction-error by this way: $e_{Th}=\{\boldsymbol{e}|\boldsymbol{e}\geq Th\}$, where $Th\geq|e_{\min}|$. Therefore, the size of distortion metrics $\|d(x,y)\|^2$ is $(e_{\max}-e_{Th})\times(e_{\max}-e_{Th})$.

In practice, one usually requires a single overall quality measure of the entire image. We use a Mean SSIM (MSSIM) index to evaluate the overall image quality

$$MSSIM(X,Y)=\frac{1}{M}\sum_{i=1}^{M}SSIM(x_i,y_i) \quad (17)$$

where X and Y are the reference and the distorted images, respectively. x_i and y_i are the image contents at the jth local window. $M$and is the number of local windows of the image. We implemented these methods on the computer with Intel core i3 and 4GB RAM. The program developing environment is MATLAB R2011b based on Microsoft Windows 7 operating system. In the experiment, in order to simplify the complexity of MSSD, let $c=10.5$. We implemented the proposed code construction with arithmetic coder as the entropy coder. In the experiment, we set the block length $K=7000$ and the length of the last block $L_{last}=4000$, and $Th=\max\{400-R\times 800, 10\}$. Test image is shown in Fig.3.

Observing form Fig.4, we compare our MSSD method with Zhang *et al.*[10]. Fig.6 illustrates that if embedding rate is larger, the effect brought by our algorithm is more obvious. Comparing with Zhang *et al.*[10], our method have gained of MSSIM is much more higher, about 0.01 to 0.02 on average. Especially under large embedding rates.

Besides, we select some images from the LIVE (Laboratory for image and video engineering)[19] database to test our MSSD algorithm. Observing form Table 1, we compare our method with Zhang *et al.*[10] method in

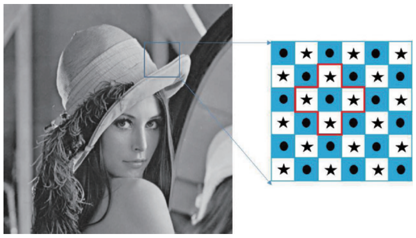

Fig. 2. The image divided into two sets: shadow pixel and the blank set

Fig. 3. Test image lena, barbara, cornfield, boat, man, cablecar

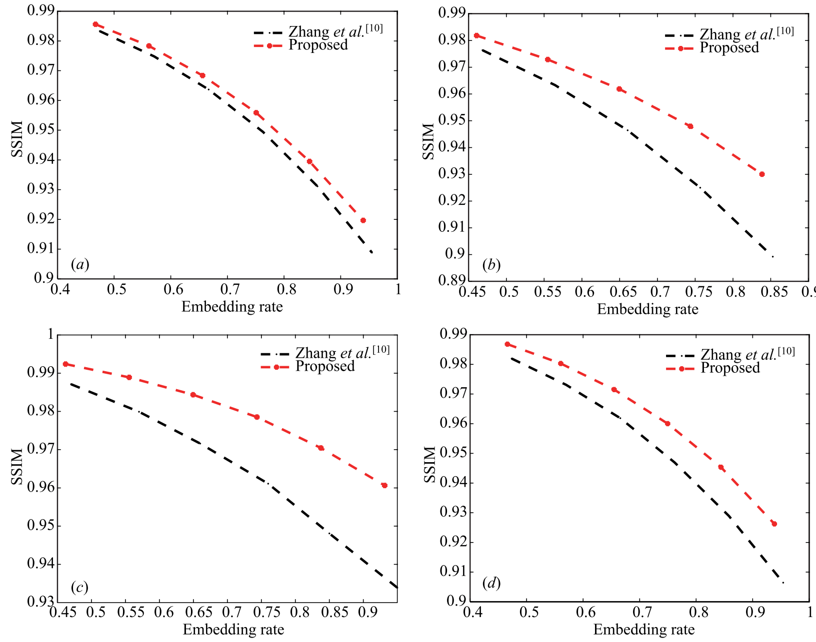

Fig. 4. Embedding performance of (*a*) Lena; (*b*) Barbara; (*c*) Cornfield; (*d*) Boat

Table 1. Embedding performance comparisons with Zhang *et al.*[10].

	Image	Embed-rate	Zhang *et al.*	Proposed	Improvement	Increased percentage
1	lena	0.96	0.9088	0.9196	0.0108	1.17%
2	barbara	0.85	0.8992	0.9300	0.0308	3.42%
3	cornfield	0.95	0.9339	0.9606	0.0267	2.86%
4	boat	0.95	0.9064	0.9262	0.0198	2.18%
5	man	0.90	0.9189	0.9324	0.0134	1.46%
6	cablecar	0.95	0.9520	0.9673	0.0153	1.61%
7	flowersonih	0.85	0.9187	0.9538	0.0351	3.82%
8	lighthouse	0.96	0.8804	0.9166	0.0362	4.11%
9	manfishing	0.95	0.9264	0.9434	0.0170	1.83%
10	sailing	0.96	0.8919	0.9167	0.0247	2.77%
11	carnivaldolls	0.95	0.9487	0.9642	0.0154	1.62%
12	house	0.96	0.9066	0.9214	0.0148	1.63%

different embedding rate. Comparing with the Zhang *et al.*[10] method, our MSSD method gains 1.17%, 3.42%, 2.86%, 2.18%, 1.46%, 1.61%, 3.82%, 4.11%, 1.83%, 2.77%, 1.62%, 1.63% in test image lena, barbara, cornfield, boat, man, cablecar, flowersonih, lighthouse, manfishing, sailing, carnivaldolls, house, respectively. For our method, an average 2.37% gains is earned compared with the Zhang *et al.* [10] method. Especially under high embedding rates. Both of this indicate that to some extent, the MSSD strategy for RDH is efficiency

IV. Conclusions

In this paper, we propose MSSD for reversible data hiding. We deduce the metric of the structural similarity constraint, and further we prove it does't hold Non-crossing-edges (NCE) property. We construct the rate-distortion function of optimal structural similarity constraint, which is equivalent to minimize the average distortion for a given embedding rate. Experiments show that our proposed ESMS method is effective.

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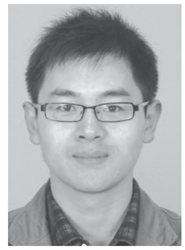

XU Jiajia was born in Bozhou. He received the B.S. degree in 2009 from the Hefei University of Technology (HFUT), and the M.S. degree in 2012 from the University of Science and Technology of China (USTC), Hefei, China. He is now pursuing the Ph.D. degree in USTC. His research interests include cloud security, image and video processing, video compression and information hiding. (Email: xujiajia@mail.ustc.edu.cn)

ZHANG Weiming received the M.S. degree and Ph.D. degree in 2002 and 2005, respectively, from the Zhengzhou Information Science and Technology Institute, Zhengzhou, China. Currently, he is an associate professor with the School of Information Science and Technology, University of Science and Technology of China, Hefei, China. His research interests include multimedia security, information hiding and cryptography. (Email: zhangwm@ustc.edu.cn)

JIANG Ruiqi received the B.S. degree in 2010 from the Harbin Institute of Technology (HIT), and the M.S. degree in 2013 from the New York University. He is now pursuing the Ph.D. degree in University of Science and Technology of China (USTC), Hefei, China. His research interests include cloud security and information hiding. (Email: jrq123@mail.ustc.edu.cn)

YU Nenghai received the B.S. degree in 1987 from Nanjing University of Posts and Telecommunications, Nanjing, China, the M.E. degree in 1992 from Tsinghua University, Beijing, China, and the Ph.D. degree in 2004 from the University of Science and Technology of China, Hefei, China, where he is currently a professor. His research interests include multimedia security, multimedia information retrieval, video processing and information hiding. (Email: ynh@ustc.edu.cn)