Image Hiding by Non-uniform Generalized LSB and Dynamic Programming

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***Abstract*— A novel steganographic method based on non-uniform generalized LSB is proposed. Different from the traditional distortion measure MSE and PSNR, the structural-similarity based image quality assessment is used to measure the distortion caused by the data hiding. With the given maximum allowable distortion, dynamic programming is performed to find the optimum substitution depth vector to achieve the maximum capacity. Experiments show the proposed method can achieve higher embedding payload while keeping smaller distortion.**

Keywords—steganography;non-uniform generalized LSB; structural similarity; dynamic programming;

Topic area—4.a. Multimedia Assurance(data hiding)

I. Introduction

Digital watermarking and steganography are two important branches of information hiding. While watermarking aiming to protect intellectual property rights of multimedia contents, the purpose of steganography is to send secrete message under the cover of a carrier signal. It is generally accepted the steganography must possess two important properties: imperceptibility and high data capacity. The first one ensures that the embedding is imperceptible (can not be detected by human eyes), and the second stands for the efficiency of the steganographic communication.

In the literatures, many techniques for data hiding have been proposed [3-7], one of the common well-known steganography method is the LSB substitution which replaces the least significant bits of pixels with the data bits. However, not all pixels in an image can tolerate equal amount of changes without causing noticeable distortion. According to the HVS, the changes occurring in smooth areas can be easily noticed by human eyes, thus the adaptive method for steganography [6,7] are introduced, in which the amount of the data embedded in pixel is variable. Although those methods devote themselves to make the as much as possible bits into the cover image while leaving the distortion unnoticeable, the hiding capacities are limited and there is no good manner to control the distortion caused by the data hiding. In this paper, we develop a method for hiding data with larger capacity. The proposed method is based on non-uniform generalized LSB substitution. By the structural-similarity based image quality assessment method, the corresponding embedding distortion is defined. With the given maximum allowable distortion, the dynamic programming is performed to find the optimum substitution depth vector and achieve the maximum embedding payload.

The remainder of the paper is organized as follows. Section II describes the details of image distortion measurement based on structural similarity. In section III, the non-uniform generalized LSB substitution method is proposed and the capacity and distortion are deduced. In section IV, the steganographic optimization problem is setup and the dynamic-programming based optimization process is described. In section V, the experimental results are presented and discussed. The conclusions are made in Section VI.

II. Structural Similarity Distortion Measurement

In the majority of prior works, to evaluate the performance of a data hiding technique, there was concentration on the implementation of MSE between the original and the stego images. Also, the PSNR, which is closely related to the MSE measure, has been extensively implemented for image quality judgment. However, these measures are not very accurate perceptually because they do not match well with the HVS characteristics. This can be attributed to the fact that the MSE criterion quantifies deviations in an image on a pixel-by-pixel basis, while the HVS tends to perceive the features of an image as a whole.

In [2], Wang et.al. presented a new numerical measure for gray scale images, called the universal image quality index, Q, which is defined as

$$Q = \frac{4\sigma_{xy}\mu_x\mu_y}{(\sigma_x^2+\sigma_y^2)(\mu_x^2+\mu_y^2)},$$

where x_i, y_i, $i=1,\ldots,n$, represent the original and distorted signals respectively, $\mu_x = 1/n\sum_{i=1}^{n} x_i$, $\mu_y = 1/n\sum_{i=1}^{n} y_i$, $\sigma_x^2 = 1/(n-1)\sum_{i=1}^{n}(x_i-\mu_x)^2$, $\sigma_y^2 = 1/(n-1)\sum_{i=1}^{n}(y_i-\mu_y)^2$, and $\sigma_{xy} = 1/(n-1)\sum_{i=1}^{n}(x_i-\mu_x)(y_i-\mu_y)$.

As described in [2], this quality index models any distortion as a combination of three factors: loss of correlation, mean distortion and variance distortion, such as

$$\frac{\sigma_{xy}}{\sigma_x\sigma_y}, \frac{2\mu_x\mu_y}{\mu_x^2+\mu_y^2}, \text{ and } \frac{2\sigma_x\sigma_y}{\sigma_x^2+\sigma_y^2}$$

The quality index Q is applied to a gray level image using a sliding window approach with a window size of 8×8. The index is computed for each window, leading to a quality map of the image. The overall quality index is the average of the all the Q values in the quality map:

$$Q = \frac{1}{M}\sum_{j=1}^{M} Q_j, \text{ M is the total number of windows}$$

Q produces unstable results when either $\mu_x^2 + \mu_y^2$ or $\sigma_x^2 + \sigma_y^2$ is close to zero. To avoid this problem, the measure has been generalized to the Structural Similarity Index (SSIM) [1]:

$$Q = SSIM(X,Y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (1)$$

Here, the constants $C_1=(K_1R)^2$, $C_2=(K_2R)^2$ and R is the dynamic range of the pixel value (255 for 8-bit gray images), and $K_1 \ll 1, K_2 \ll 1$. The author also uses the circular-symmetric Gaussian weighting function with standard deviation of 1.5 to avoid the undesirable "blocking" artifacts.

The dynamic range of Q is [-1,1], with the best value 1 achieved when $y_i = x_i, i = 1, 2, ..., n$. So the distortion can be defined as

$$D(X,Y) = 1 - SSIM(X,Y) \quad (2)$$

In this paper, different from the computation in [2] that the square block is moved pixel-by-pixel over the entire image, the computation based on non-overlapping 8×8 square blocks is used. It does not also speed and simplify the computation but facilitate the estimation caused by data hiding.

III. Non-uniform Generalized LSB Substituion

A. Embedding Method

In the traditional LSB substitution, the least significant bit of each signal sample is replaced by a payload data bit. If additional capacity is required, two or more LSBs may be overwritten on per sample; while during extraction, these bits are read in the same scanning order, which may be controlled under some key to enhance the security of the algorithm. If the host signal is represented by a vector x, the non-uniform generalized LSB embedding and extraction process can be represented as:

$$\begin{aligned} y &= Q_L(x) + s \\ s &= y - Q_L(y) = y - Q_L(x) \end{aligned} \quad (3)$$

Here, y represents the stegosignal containing the embedded information s, and

$$Q_L(x) = q_i \left\lfloor \frac{x_i}{q_i} \right\rfloor, i = 1, ..., N, q_i = 2^{l_i} \quad (4)$$

It is a non-uniform scalar quantization function, and $\lfloor \bullet \rfloor$ represents the operation of truncation to the integer part. The vector $L = \{l_i, i = 1, ..., N\}$ is called the substitution depth vector. During hiding, the lowest l_i bits of signal samples are replaced by the data bits. During extraction, the message is read from the lowest l_i bits of the stegosignal. The traditional LSB modification can be considered as the special case when $L = \{l_i = 2, i = 1, ..., N\}$.

But, it is unnecessary to use the different l_i for each pixel because the pixels in a local region may have approximately equal gray value and the same image characters, such as the texture, edges and so on. We can divide the image into some local blocks and use the same l_i for pixels in a block and the different l_i for the different block. So the substitution depth vector can be written as

$$L = [\underbrace{k_1, ..., k_1}_{m_1}, ..., \underbrace{k_i, ..., k_i}_{m_i}, ..., \underbrace{k_M, ..., k_M}_{m_M}], m_1 + ... + m_M = N$$

In the proposed scheme, the whole image is divided into amounts of square 8×8 non-overlapped blocks, which consistent with the computation of SSIM. It means m_i=64, i=1,…,N/64. For simplicity, L is written as $L = [k_1, k_2, ..., k_M]$ to block-based non-uniform case.

B. Capacity of the Non-uniform Generatlized LSB

In the proposed embedding method, each signal can carry l_i bits; therefore, the embedding capacity can be denoted by the average payload of all image pixels. Considering the block-based non-uniform scheme is used in the paper, so the capacity can be written as

$$C(L) = \frac{1}{N}\sum_{i=}^{N} l_i = \frac{1}{N}\sum_{i=1}^{M} 64k_i \quad (5)$$

In the practical application, before the extraction of the message, the decoder should know the additional information about the substitution depth vector L used in data hiding in advance. To realize the blind extraction, i.e. without the aid of the extra side information, L must be embedded into the image. Because the possible maximum substation depth is 7, we can use three bits of one block to carry the substitution depth k_i. The three bits can be chosen from 64 LSBs of block pixels controlled by some key to ensure the security of the whole system, and these bits to carry the substitution depth vector should be skipped during data hiding. Therefore, the available capacity is $\frac{1}{N}\sum_{i=1}^{M}(64k_i - 3)$.

C. Distortion Caused by the Non-uniform Generalzied LSB

Suppose the cover image X is embedded by the binary message S using the substitution depth vector L, the structural similarity measurement of the cover image and stegoimage is *SSIM(X,L,S)*. According to Eq. (2), the distortion is

$$D(X,L,S) = 1 - SSIM(X,L,S) \tag{6}$$

It is obvious that the distortion is the function of substitution depth vector L and binary message S. But in the practical application, the message bits to be hidden are not determined in advance. Therefore, the expected distortion of different S is used to evaluate quality loss because of data hiding, which is shown in Eq. (7).

$$D(X,L) = E_S(D(X,L,S)) = 1 - E_S(SSIM(X,L,S) \tag{7}$$

According to the description in Section II, $D(X,L)$ can be computed block-by-block. Suppose, in a local block B, the corresponding substitution depth is k, $Q_k(B)$ is $\overline{B}$ and the embedded message is s, then

$$E_s(SSIM(B,B(k,s)) = E_s\left[\frac{(2\mu_B\mu_{\overline{B}+s}+C_1)(2\sigma_{B(\overline{B}+s)}+C_2)}{(\mu_B^2+\mu_{\overline{B}+s}^2+C_1)(\sigma_B^2+\sigma_{\overline{B}+s}^2+C_2)}\right] \tag{8}$$

Because s is irrelevant to B and $\overline{B}$, so Eq. (8) is equal to

$$E\left[\frac{(2\mu_B\mu_{\overline{B}}+2\mu_B\mu_s+C_1)(2\sigma_{B\overline{B}}+C_2)}{(\mu_B^2+(\mu_{\overline{B}}+\mu_s)^2+C_1)(\sigma_B^2+\sigma_{\overline{B}}^2+\sigma_s^2+C_2)}\right]$$

It is appropriate to suppose the embedded binary bit obeys uniform distribution on {0,1}, because the message is usually compressed and encrypted before embedding. When using the binary message substitute the k least significant bits of the local block pixels, it is obvious that s obeys the uniform distribution on $\{0,1,..,2^k\text{-}1\}$,which means $\mu_s = (2^k-1)/2$ and $\sigma_s = \sqrt{(2^k-1)^2/12}$. Therefore, Eq. (8) is finally equal to

$$\frac{(2\mu_B\mu_{\overline{B}}+\mu_z(2^k-1)+C_1)(2\sigma_{B\overline{B}}+C_2)}{(\mu_B^2+(\mu_{\overline{B}}+(2^k-1)/2)^2+C_1)(\sigma_B^2+\sigma_{\overline{B}}^2+(2^{k_i}-1)^2/12+C_2)}$$

IV. Finding The Optimum Subtitution Depth Vector By Dynamic Programming

A. *Setup the Optimization Problem*

According to the equation (8), the distortion is the function of the substitution depth vector L. Suppose $D(X,L) \le \varepsilon$, ε must be very small value to keep the visual quality of image not being destroyed by the data hiding. To get the maximum embedding capacity under the given maximum allowable distortion is equal to resolve the following optimization problem.

$$\max_L C(L) = \frac{1}{N}\sum_{i=1}^{N} l_i = \frac{1}{N}\sum_{i=1}^{M}(64k_i - 3) \tag{9}$$
$$s.t.\ D(X,L) = 1 - E(SSIM(X,L,S)) \le \varepsilon$$

B. *Finding the Optimum Subsitution Depth Vector by the Dynamic Programming*

To resolve the optimization problem (9), we firstly use the penalty function to convert the constrained optimization problem to unconstrained one. After addition of the penalty function to the optimization object, the problem (9) changes to

$$\max_L f(X,L) = C(L) + P\cdot\max[0, D(X,L)-\varepsilon].$$

Here, P is a large negative value. Let P is equal to -10000 to make the penalty when the distortion caused by embedding using L exceeds the allowable ε.

The above problem can be resolved by dynamic programming. At the beginning, the optimization process is partitioned into successive stages. In each stage, the decision is to choose the optimum k_i of L to increase one, and the state of each stage is the corresponding L. The process to find the optimum L can be described as:

- STEP 1. Input the cover image X and initiate the substitution depth vector $L^0 = [0,...,0]^M$, the dimension M of L is determined by the image size and the size of square block. For an m×n gray image and the 8×8 square block, the dimension $M = mn/64$.
- SETP 2. For the ith stage, Let $L' = L^i + [1,...,1]^M$, according to equation (8), compute the local distortion change,

$$dD_j = D_j(X,L') - D_j(X,L^i),\ j = 1,...,M.$$

Then, choose the optimum position j^* according to the below equation

$$j^* = \min_j \frac{|dD_j(X,L',L^i)|}{D_j(X,L^i)^\alpha},\ j = 1,...,M. \tag{10}$$

It means to find the least distortion change block to increase the substitution depth, i.e. the capacity. The dominator of the above equation is to avoid excessive destroys in one local block. In the paper, we choose α equal to 2. Then L'' can be obtained by the below equation.

$$L'' = [k_1^i,...,k_{j^*}^i+1,...,k_N^i]$$

- STEP 3. Compute the values $f(X,L'')$ and $f(X,L^i)$. If $f(X,L'') > f(X,L^i)$, let L^{i+1} be L'' and go to STEP 2, else stop the finding and output the optimum substitution depth vector L.

V. Experiments Results and Discussions

In our experiments, four standard test images "Lena", "Jet", "Peppers" and "Baboon" are used, each with size 512×512. The first experiment is performed with the maximum allowable distortion equal to 0.03. Two of the four stegoimages and the corresponding substitution depth vector map are shown in Fig.1. Set the maximum allowable distortion be 0.01 and 0.04, the second experiment is done and the results are shown in TABEL.I. The third experiment is to evaluate the relationship between the maximum capacity and the maximum allowable distortion with ε constrained in the range of [0.001, 0.03]. The image, Lena, is used to make the test and the relationship is shown in Fig.2.

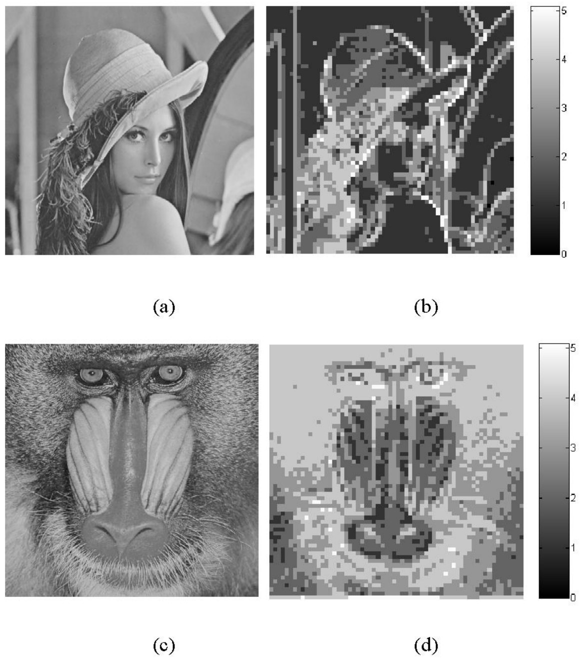

Figure 1. Two of stegoimages and the corresponding substitution depth vector map with the given maximum allowable distortion equal to 0.03.
(a).stegoimage of lena (b).the substitution depth vector map of Lena
(c).stegoimage of Baboon (d).The substitution depth vector map of Baboon
(the colorbars of (b) and (d) stand for the substitution depth)

From Figure 1, we can see most of information is embedded into the edges and textures of the images. These distortions will be less noticeable because the changes in edge and texture parts of image are generally less obvious to human eyes.

TABLE I. MAXIMUM CAPACITY WITH DIFFERENT MAXIMUM ALLOWABLE DISTORTION

Cover image	**Maximum Capacity**	
	$\varepsilon = 0.01$	$\varepsilon = 0.04$
Lena	1.5664	2.4043
Baboon	2.6133	3.5625
Jet	1.7520	2.5664
Peppers	1.8281	2.7012

It is shown in TABLE I that the images with more edges and textures can carry more information than the flat one.

From Figure 2, with the increase of the maximum allowable distortion, the capacity increases correspondingly, while the speed becomes slow. Under a concrete application situation, one can choose a proper point from the curve to make a good combination of the distortion and capacity.

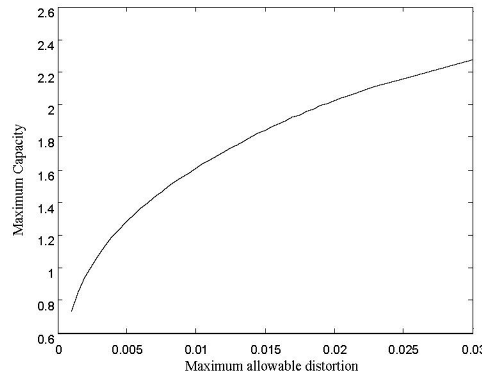

Figure 2. The relationship between the maximum allowable distortion and the maximum capacity of the image Lena.

VI. CONCLUSIONS

In this paper, the similarity-structural based image quality measurement method is used to measure the distortions caused by the information hiding. With the given maximum allowable distortion, the dynamic programming is used to find the optimal substitution depth vector for non-uniform generalized LSB to achieve the maximum hiding capacity. The experimental results reveal the practicability and superiority of the presented techniques.

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