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AN ENTROPY BASED TECHNIQUE FOR INFORMATION EMBEDDING IN IMAGES

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ABSTRACT

Many information hiding techniques have recently been analyzed as they could help manage part of the digital rights. Among the general framework of information hiding, the focus has been put on steganography and on watermarking techniques.
This paper proposes an entropy based technique for data embedding in images with a specific target, sometimes referred to as *feature location*: inclusion of a maximum amount of information instead of robustness against attacks.
After an introduction, we analyze the error that results from a modification of the least significant bits. Then we describe our embedding technique. Finally we examine the upper bound of information that can be embedded in the least significant bits by means of our technique and we conclude.

1. INTRODUCTION

Digital representation of media has the undesirable effect to increase the opportunity for violation of copyright or illegal copying. In order to counter this effect, providers of digital content have stimulated the development of techniques that protect some digital rights. Some people believe that data hiding could solve the question of content protection, but according to the current state of the art there is no definitive answer yet (see [2]).
Data hiding techniques are processes that embed data, such as copyright information, with a minimum amount of degradation to the host signal, called *cover* and denoted C hereafter. For images, the embedded data should be invisible. Psychovisual metrics have intensively been used to ensure that a modified image remains visually identical to the original image. Amongst others, MASRY *et al.* [3] proposed a technique based on a wavelet decomposition. It is worth mentioning that data embedding does not necessarily introduce irreversible degradations of an image. HONSINGER *et al.*[4] and FRIDRICH *et al.* [5] have proposed lossless data embedding techniques that allow the recovery of the original image.
Possible additional requirements for data hiding could be robustness to image modifications –this is the domain of the sometimes confusingly called watermarking techniques–, undetectability, etc. As long as the embedded signal remains invisible there is no upper bound to the amount of embedded information but the larger the amount of information the easier it is to detect the presence of an embedded signal; this might be undesirable when dealing with watermarking [6].
In this paper we propose a technique that insert a maximum amount of information in a raster image. Our technique has the following properties:

- The modified image is subjectively identical to the original image. Although we did not perform an exhaustive set of tests, we encountered no case where a difference was noticeable.
- The data is directly embedded in the image, rather than into a header.
- The embedded data is *self-detectable*. This means that there is no need to put any specific information in the header or elsewhere.
- The embedding technique allows the inclusion of a maximum amount of information with respect to the image content. The principle is that, in practice, the amount of information will depend on the randomness of the image. The higher the randomness the higher the amount of information that can be embedded in the image.
- The embedded information offers a service to the user. Therefore there is no reason to remove or alter the embedded information.

These properties are similar to the properties of *feature location* techniques as defined by BENDER *et* al. [7] with one major difference in that we want to put a maximum amount information in an image.

2. EMBEDDING INFORMATION IN THE LEAST SIGNIFICANT BITS: ERROR ANALYSIS

We suppose that the information is exclusively embedded in the least significant bits of each pixel value by substitution.

It is well known that least significant bitplanes of natural images tend to look random; this is illustrated on *Lena* in Figure 1. In higher bitplanes neighboring pixels are statistically highly correlated.

Techniques that substitute bits generally assume that values are uncorrelated in least significant bitplanes in order to hide or embed a signal. However, as pointed by FRIDRICH *et al.*[8], it is possible to reliably detect the presence of a pseudo-random signal embedded in the least significant bits of a color image due to the existence of typical distributions of color values in natural or artificial images. The detection mechanism is especially efficient when bitplane values are more correlated than the embedded signal.

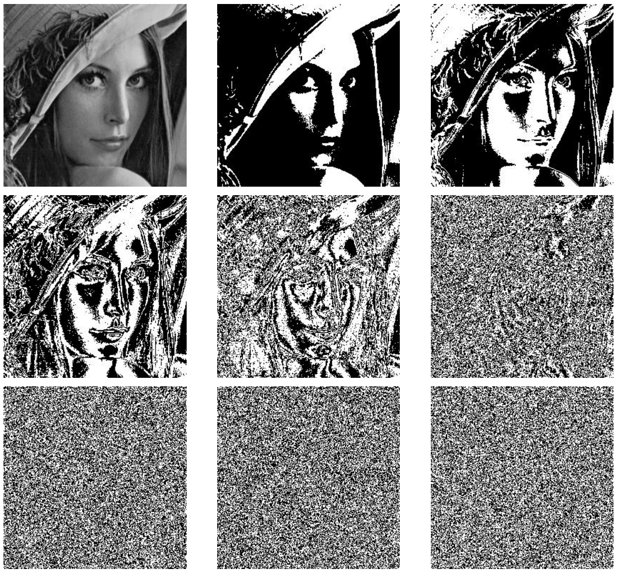


Figure 1: *Lena* and her bitplanes (c_7, ..., c_0) starting from the most significant bit.

We now examine the impact of modifying bitplane values for a given error function. Let $c(x, y)$ denote the 8-bits value of pixel (x, y) of the cover. The image resulting from data embedding is denoted $f(x, y)$. We define the error as the function $e(x, y) = c(x, y) - f(x, y)$. As mentioned in the introduction, the highest bitplanes exhibit some similarities with the gray level image, but the least significant bitplanes look random. In the following, bitplanes are supposed to be independent and to be the realization of a stationary ergodic process.

We can not assume that the probabilities of a 0 or a 1 of bits in each bitplane of the cover, denoted respectively $p_c(0)$ and $p_c(1)$, are equal to $\frac{1}{2}$. However the probabilities of a 0 or a 1 of the embedded data $i(x, y)$, denoted $p_d(0)$ and $p_d(1)$, should be equal to $\frac{1}{2}$ in order to maximize the amount of bits of information put inside the cover. For convenience, we use the probabilities as provided in Table 1.

Probability	$p_c(0)$	$p_c(1)$	$p_d(0)$	$p_d(1)$
Value	α	$1-\alpha$	$\frac{1}{2}$	$\frac{1}{2}$

Table 1: Summary of notations and assumptions concerning the probabilities for 0s and 1s.

Thanks to the assumptions of stationarity, ergodicity and bitplane independence, the error can be written as a random variable $e = e_0 + 2e_1 + 4e_2 + \ldots = (c_0 - i_0) + 2(c_1 - i_1) + 4(c_2 - i_2) + \ldots$ where e_k represents the error in bitplane k. The mean, variance, and Mean Square Error (MSE) of e_k are respectively equal to (after some calculation):

$$\mu_{e_k} = \tfrac{1}{2} - \alpha, \qquad \sigma_{e_k}^2 = -\alpha^2 + \alpha + \tfrac{1}{4},$$
$$MSE_k = \sigma_{e_k}^2 + \mu_{e_k}^2 = \tfrac{1}{2}$$

These functions are drawn in Figure 2.

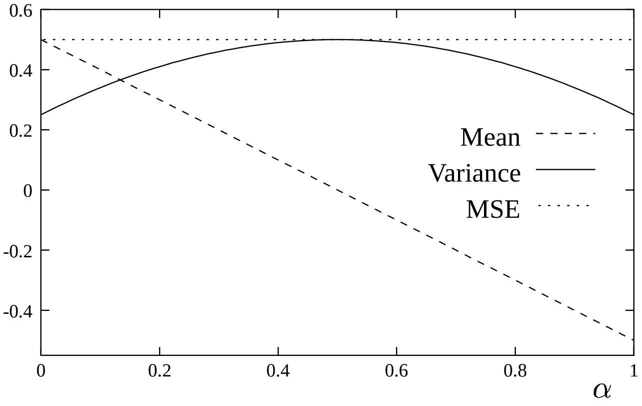


Figure 2: μ_{e_k}, $\sigma_{e_k}^2$ and MSE_k as functions of α.

It appears that MSE_k does not depend on the cover, but the mean and the variance do. A general remark is that although 1 bit of information has been included in the cover, the error is not equal to 1 bit on average. This results from situations where the embedded bit is equal to the original bit.

It is now possible to derive σ_e^2 from the $\sigma_{e_k}^2$. Indeed, as a result of the independence between the bitplane values, $\sigma_e^2 = \sigma_{e_0}^2 + 4\sigma_{e_1}^2 + 16\sigma_{e_2}^2 + \ldots = \sum_{k=0}^{n-1} 2^{2k}\left(-\alpha_k^2 + \alpha_k + \frac{1}{4}\right)$ where n is the number of least significant bits that have been substituted. In the case of $p_c(0) = p_c(1) = \frac{1}{2}$, which is a assumption usually valid on the least significant bits of a natural image, $\sigma_e^2 = \frac{4^n - 1}{3} \times \frac{1}{2} = \frac{4^n - 1}{6}$. This expression shows that σ_e^2 exponentially increases with n.

3. DESCRIPTION OF AN ENTROPY BASED EMBEDDING TECHNIQUE

Our embedding technique is based on the modification of the least significant bits. In order not to compromise the overall image quality, the algorithm adapts the number of embedded bits to the image content. The steps of the algorithm are the following (we assume that the image is defined on 8 bits):

1. the image is divided in 8×8 pixels wide blocks.

2. for each 8×8 block, denoted B, compute the entropy $H(B)$ on the 4 most significant bits. If the entropy is larger than 2, then embed information in the 4 least significant bits of B, else go to step 3.

3. for each block compute the entropy $H(B)$ on the 5 most significant bits. If the entropy is larger than 2 then embed information in the 3 least significant bits of B, else embed information in the 2 least significant bits of B.

Because the entropy computed during step 2 is based on the 4 most significant bits, there are only 16 possible values and therefore the entropy is contained in the $[0, 4]$ interval. The threshold of 2 was chosen to be in the middle of this interval. The entropy computed during step 3 is different from that of step 2 as the computation is based on 5 bits; accordingly the entropy is contained in $[0, 5]$. In all cases, the algorithm provides a minimum of 2 embedded bits per pixel. But in the best case, the number may raise to 4 bits.

At the reception side, a similar algorithm is used in order to extract the embedded message:

1. the image is divided in 8×8 pixels wide blocks.

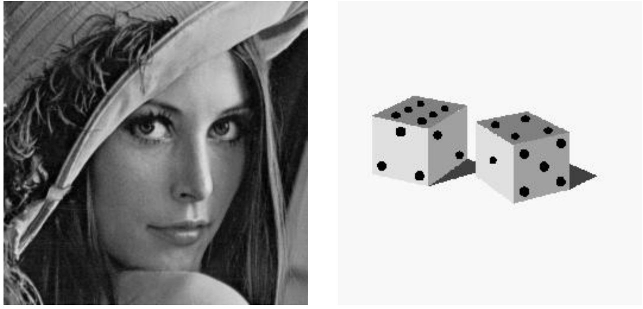
2. for each 8×8 block, compute the entropy $H(B)$ on the 4 most significant bits. If the entropy is larger than 2, then retrieve the 4 least significant bits of B, else go to step 3.

3. for each block compute the entropy $H(B)$ on the 5 most significant bits. If the entropy is larger than 2 then retrieve the 3 least significant bits of B, else retrieve the 2 least significant bits of B.

Figure 3 shows images and several statistics like the original size, the entropy per pixel $H(C)$ and the maximal size of the message that might be embedded. The last row provides the average number of embedded bits per pixel. In the case of the *Dice* image, the upper size of the embedded image is exactly equal to 2 bits per pixel as could be expected.

Because the algorithm adaptively determines the number of bits to embed based on the image content, we expect no subjective difference between an original image and that image after information embedding; however, this assumption has not been tested on an exhaustive list of image samples. Illustrations on *Lena* and *Dice* are provided in Figure 4 (the message was generated randomly).

Lena $65,536\ [bytes]$ *Dice* $65,536\ [bytes]$

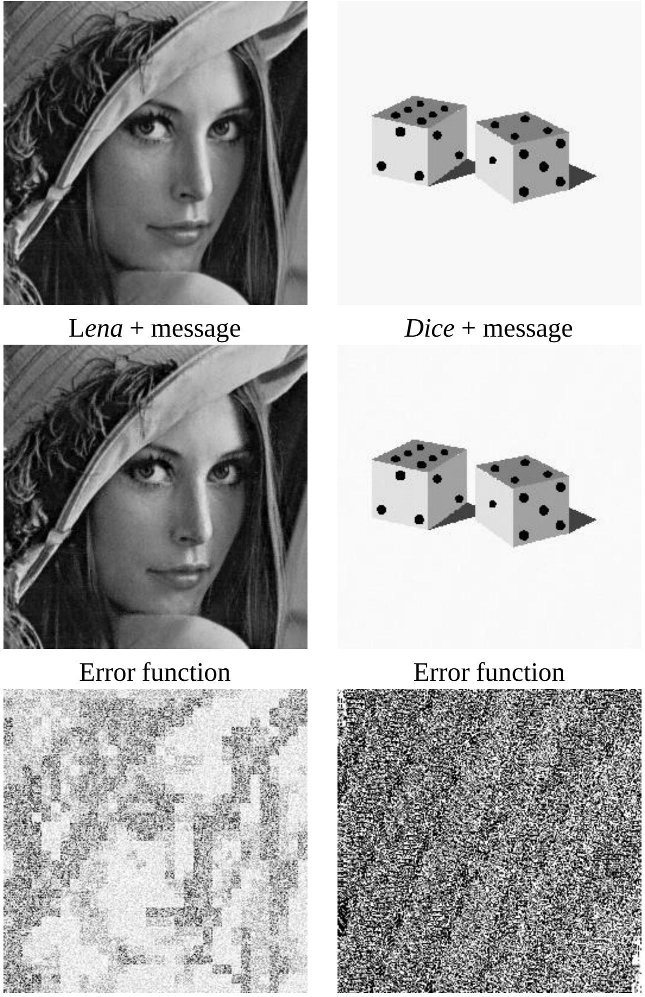


$H(C) = 7.52$
Message = $25,048\ [bytes]$
Message = $3.06\ [bit/pixel]$

$H(C) = 0.96$
Message = $16,384\ [bytes]$
Message = $2\ [bit/pixel]$

Figure 3: Images and sizes of the message that can be embedded.

Lena $65,536\ [bytes]$ *Dice* $65,536\ [bytes]$



L*ena* + message *Dice* + message

Error function Error function

Figure 4: Illustrations of our embedding technique.

4. DETERMINATION OF THE UPPER BOUND OF INFORMATION THAT CAN BE EMBEDDED

Real applications require to know in advance the number of bits that can be embedded in an image. As this number depends on the image content, it is impossible to provide a general upper bound. One possible practical solution could consist in the use of curves that plot the average number of embedded bits as a function of the entropy of the cover $H(C)$, for a set of typical images (photographs, graphics, etc). In order to provide an upper bound, we used an image in which values were generated by a gaussian process $N(127.5, \sigma_N^2)$ centered on 127.5. All values were rounded to the closest integer in $[0, 255]$.

Figure 5 shows the evolution of the number of bits that our algorithm would embed in a gaussian generated image as a function of σ_N^2, expressed in decibels $[dB]$. The link between $H(C)$ and the upper bound is plotted in Figure 6.

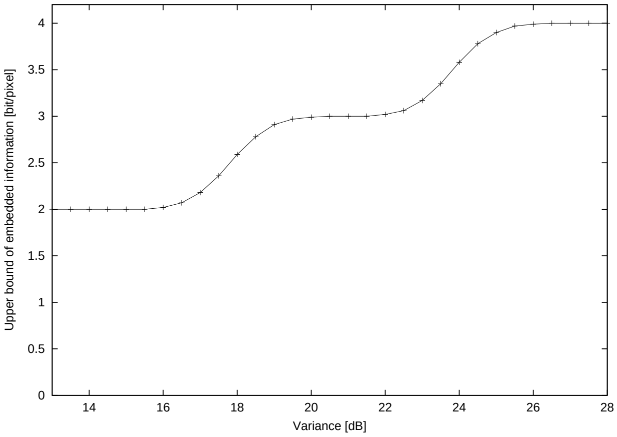


Figure 5: Link between σ_N^2 and the average upper bound of embedded bits per pixel.

Both Figure 5 and 6 show the presence of 2 steps. These steps result from our thresholding technique. If needed softer thresholding techniques could lead to a linear behavior in the critical zone.

5. CONCLUSIONS

In this paper we proposed a technique to embed information based on the local entropy computed on each 8×8 block. The algorithm, described in section 3, adaptively adjusts the number of bits to be included based on a variable number of most significant bits. At the reception side, a similar algorithm extracts the embedded signal without the need of additional information. In section 4 we have provided a practical upper bound for the amount of information that can be embedded in an image with our technique.

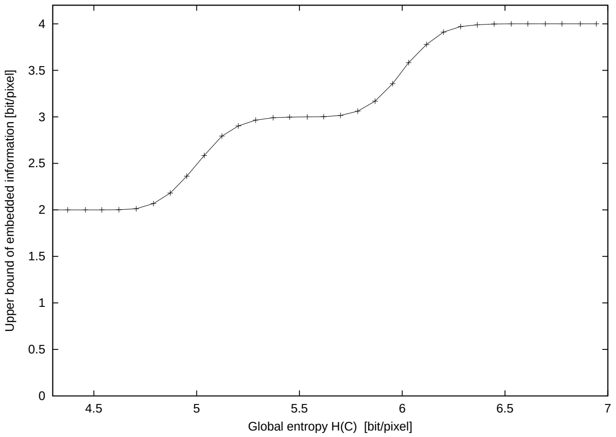


Figure 6: Link between the entropy of the cover $H(C)$ and the average upper bound of embedded bits per pixel.

6. REFERENCES

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