

STATISTICAL DETECTION OF INFORMATION HIDING BASED ON ADJACENT PIXELS DIFFERENCE

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ABSTRACT

This paper presents a novel methodology for statistical detection of Least Significant Bits (LSB) matching steganography. It proposes to exploit a statistical model of natural images adjacent pixels difference. In this paper, the detection problem is first addressed in a theoretical context when cover image parameters are known. The most powerful likelihood ratio test (LRT) is designed and its statistical performances are analytically expressed. Then, for a practical case of unknown image analysis, an estimation of distribution parameters is proposed to designed a test whose performance are also analytically established. Numerical results on a large image database shows the relevance of proposed methodology.

Index Terms— Hypothesis testing, Data hiding, Information forensics, Detection theory, Image processing.

1. INTRODUCTION AND CONTRIBUTIONS

Steganography aims to provide a covert communication channel by hiding a secret information into a host digital medium. Many steganographic tools are easily available on the Internet putting steganography within the reach of anyone. The detection of such information hiding techniques has thus become a crucial problem. In an operational context, the detection of simple but often found steganographic scheme is very important. The vast majority of common steganographic tools embeds hidden information in the LSB plane. Hence, many different methods have been proposed to detect information hidden in the LSB of digital media, see [1]. Among the two LSB steganographic scheme, considerable progress have been made for the detection of LSB replacement whereas detection of LSB matching scheme remains a challenging problem [2].

The detectors dedicated to LSB matching steganography can be roughly divided into two categories. Most of the latest detector are based on supervised machine learning methods [2]. On the opposite, it has been observed that LSB matching acts as a low-pass filter on medium histogram ; this finding leads to the family of histogram based detectors [2, 3].

In an operational context, proposed detector must be immediately applicable without any training phase. Moreover,

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the most important challenge is to propose a detection algorithm with analytically predictable probabilities of errors which remains an open problem of machine learning. For these reasons, machine learning based detectors are to proscribe. Histogram-based detector are interesting, but these *ad hoc* methods have been designed without using a statistical cover model and hypothesis testing theory. Hence, their statistical performance can only be approximated by simulation.

An alternative approach is to design a test with known theoretical properties by using decision theory with a model of cover media. The first step in this direction have been proposed in [10, 4]. In this paper, this methodology is used with an original statistical model of natural images which prevents occurrence of nuisance parameters. The original contribution is threefold: 1) A statistical model of adjacent pixels difference is used in order to avoid dealing with nuisance parameters. 2) The most powerful (MP) LRT is designed and its statistical performances are analytically calculated. 3) Based on the LRT, an efficient test is proposed when distribution parameter have to be estimated and its statistical performances are established. Numerical experimentation shows that proposed test outperforms the state-of-the-art detectors.

The paper is organized as follows. Section 2 presents the used statistical model of cover image. The problem of LSB matching detection is stated in Section 3. The optimal LRT is presented and its performances are calculated in Section 4. Finally, proposed test based on distribution parameter estimation is presented in Section 5 and its performance are analytically established. The relevance of proposed approach is emphasized through numerical experimentation presented in Section 6 and Section 7 concludes the paper.

2. STATISTICAL MODEL OF MEDIA

This paper mainly focuses on natural images though the proposed methodology can be applied for any kind of digital media as long as present statistical model holds. Hence, let the column vector $\mathbf{C} = (c_1, \dots, c_N)^T$ represents a cover image of $N = N_x \times N_y$ grayscale pixels. The set of grayscale level is denoted $\mathcal{L} = \{0; \dots; 2^B - 1\}$ as pixels values are usually unsigned integer coded with B bits. Each cover pixel c_n results from the quantization: $c_n = Q(y_n)$ where $y_n \in \mathbb{R}^+$ denotes the raw pixel intensity recorded by the camera and Q represents the uniform quantization with unitary step:

$$Q(x) = k \Leftrightarrow x \in [k - 1/2; k + 1/2[.$$

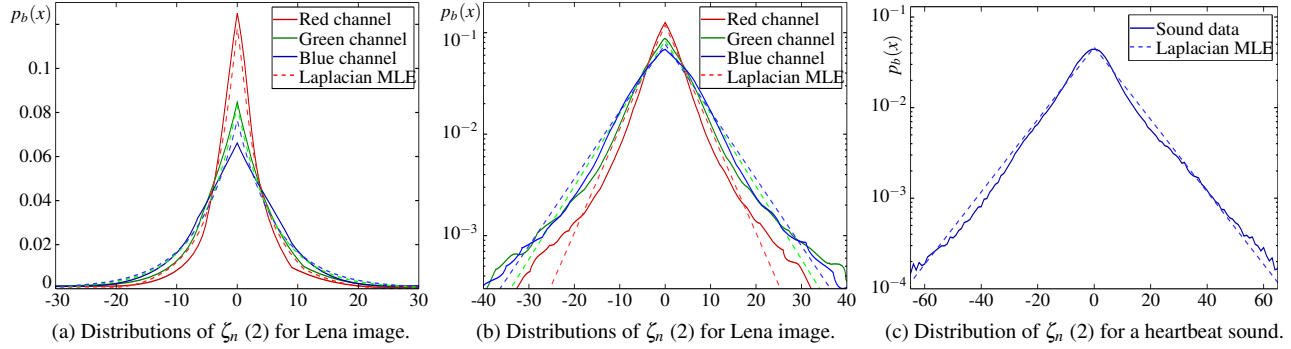


Fig. 1: Comparison between empirical distribution of $\zeta_n(2)$ and proposed Laplace model (3) with ML estimation parameter b .

In [4] it is proposed to model each RAW image pixel as an independent Gaussian random variable:

$$y_n = \theta_n + \xi_n \sim \mathcal{N}(\theta_n, \sigma_n^2), \quad (1)$$

where θ_n is a deterministic parameter and ξ_n is a zero-mean Gaussian noise representing all the noises corrupting the medium. The mean vector $\theta = (\theta_1, \dots, \theta_N)^T$ acts as nuisance parameters for detection of LSB steganography. It is especially shown in [4] that unsuitable estimation of θ may cause a high loss of detection power while estimation of θ remains an open problem in image processing. Moreover, model (1) assumes that pixels are statistically independent. This hardly holds for rendered image which have been processed by digital camera. Therefore, it is proposed in this paper to exploits a rather simple natural image statistical model which avoids dealing with complex nuisance parameters.

The post-acquisition processes, see [5, 8], make pixels highly correlated with its neighbors. This fact was used in steganalysis to design features for machine learning based detectors [6]. Previous researches have proposed to statistically model adjacent pixels difference using Bessel K forms, generalized Laplacian of generalized Gaussian distributions [7]. Though the theoretical foundations of such models remains opaque, it is proposed in this paper to use adjacent pixels difference. For the sake of clarity, let us define ζ_n as follows:

$$\zeta_n = \xi_{n+1} - \xi_n, \quad \forall n \in \{1, \dots, N-1\}, \quad (2)$$

which represents the difference between adjacent pixels noise. Seeking simplicity, it is assumed that for all n , $\zeta_n \in \mathbb{R}$ is a stochastic term which follows a zero-mean Laplacian distribution, denoted P_b , whose probability density function (pdf) p_b is:

$$\forall x \in \mathbb{R}, p_b(x) = \frac{1}{2b} \exp\left(-\frac{|x|}{b}\right), \quad (3)$$

where b is the scale parameter of Laplacian distribution.

As discussed in [8, 9], the Laplacian distribution could possibly be replaced by a more accurate one. Figures 1 show a comparison between empirical distribution of ζ_n and maximum likelihood estimation (MLE) of Laplacian distribution for Lena image (Figures 1a and 1b) and for a recorded heartbeat sound (Figure 1c). Obviously, Laplacian distribution is a rather accurate model of observations.

To statistically model stego-images, the two following assumptions are usually used [2, 3]: 1) each cover pixel has the same probability of being used to hide a secret bit and 2) the message $\mathbf{M} = (m_1, \dots, m_L)^T$ is compressed or cyphered, each hidden bit m_i thus follows a binomial distribution $\mathcal{B}(1, 1/2)$. Let the embedding rate R be defined as the number of hidden bits per pixel: $R = L/N$. The LSB matching scheme consist in randomly incrementing or decrementing each pixel value whose LSB differs from the bit to be inserted. Hence, using the two previous assumptions, a short algebra shows that after insertion at rate R the stego-image $\mathbf{S} = (s_1, \dots, s_N)^T$ verifies:

$$\begin{cases} \mathbb{P}[s_n = c_n] &= 1 - R/2, \\ \mathbb{P}[s_n = c_n - 1] &= R/4 = \mathbb{P}[s_n = c_n + 1]. \end{cases} \quad (4)$$

It thus follows from Equations (3) and (4) that after insertion at rate R , the stochastic term $\zeta_n^R(2)$ follows a distribution denoted $Q_{R,b}$ whose pdf is given, for all $x \in \mathbb{R}$, as:

$$q_{R,b}(x) = \frac{R^2}{16} (p_b(x-2) + p_b(x+2)) + \left(\frac{R}{2} - \frac{R^2}{4}\right) (p_b(x-1) + p_b(x+1)) + \left(1 - R + \frac{3R^2}{8}\right) p_b(x). \quad (5)$$

3. DETECTION PROBLEM STATEMENT

Let $\mathbf{Z} = \{z_n\}_{n=1}^N$ denotes an inspected image, which is either a cover or a steganographic image. It follows from distributions (3) and (5) that the hypothesis testing problem of LSB matching steganalysis consists in choosing between:

$$\begin{cases} \mathcal{H}_0 = \{z_n \sim P_b, b \in \mathbb{R}^+, \forall n=1, \dots, N\} \\ \mathcal{H}_1 = \{z_n \sim Q_{R,b}, b \in \mathbb{R}^+, 0 < R \leq 1, \forall n=1, \dots, N\}. \end{cases} \quad (6)$$

The goal is to find a test $\delta: \mathcal{Z}^N \mapsto \{\mathcal{H}_0; \mathcal{H}_1\}$ which accepts hypothesis \mathcal{H}_i if $\delta(\mathbf{z}) = \mathcal{H}_i$ (see details on hypothesis testing in [11]). Let the class of tests with a false-alarm probability upper-bounded by α_0 be

$$\mathcal{H}_{\alpha_0} = \left\{ \delta : \sup_{b \in \mathbb{R}^+} \mathbb{P}_0(\delta(\mathbf{z}) = \mathcal{H}_1) \leq \alpha_0 \right\}, \quad (7)$$

with $\mathbb{P}_j(A)$, $j = \{0; 1\}$ the probability of event A under hypothesis j . The power function $\beta_{R,b}(\delta)$ associated with test δ is the probability of correct detection:

$$\beta_{R,b}(\delta) = \mathbb{P}_1(\delta(\mathbf{z}) = \mathcal{H}_1),$$

which, of course, depends on rate R and parameter b .

When parameter R and b are known, the problem (6) is to choose between two simple hypotheses. In such a situation, it follows from Neyman-Pearson lemma [11, theorem 3.2.1], that the MP test over the class \mathcal{H}_{α_0} is the LRT defined by the following decision rule

$$\delta^{\text{np}}(\mathbf{Z}) = \begin{cases} \mathcal{H}_0 & \text{if } \Lambda^{\text{np}}(\mathbf{Z}) \leq \tau_{\alpha_0}, \\ \mathcal{H}_1 & \text{if } \Lambda^{\text{np}}(\mathbf{Z}) > \tau_{\alpha_0}, \end{cases} \quad (8)$$

$$\text{with } \Lambda^{\text{np}}(\mathbf{Z}) = \sum_{n=1}^{N-1} \Lambda^{\text{np}}(\zeta_n) = \sum_{n=1}^{N-1} \log \left(\frac{q_{R,b}(\zeta_n)}{p_b(\zeta_n)} \right), \quad (9)$$

and τ_{α_0} is the solution of equation $\mathbb{P}_b[\delta^{\text{np}}(\mathbf{Z}) > \tau_{\alpha_0}] = \alpha_0$, to insure that $\delta^{\text{np}} \in \mathcal{H}_{\alpha_0}$.

However, in practice, neither the embedding rate R nor the scale parameter b are known. In this situation, two difficulties occur. First, an estimation procedure of b is required to design a Generalized LRT (GLRT). Second, the hypotheses (6) do not admit a monotone likelihood ratio. As a consequence, the existence of a UMP test, which maximizes the power $\beta_{R,b}$ uniformly with respect to the rate R , is compromised.

The maximum likelihood estimation of parameter b is possible to overcome the first difficulty. On the opposite, the design of an optimal test for any rate R is a difficult problem which lies outside the scope of present paper. Indeed the main goal of this paper is first, to calculate the detection performance of LRT (Section 4) and, second, to design a sub-optimal GLRT whose statistical performance are also analytically established (Section 5).

4. LIKELIHOOD RATIO TEST (LRT) FOR SIMPLE HYPOTHESIS

The calculation of LRT statistical properties requires to define the distribution of LR $\Lambda^{\text{np}}(\mathbf{Z})$. In the present paper, it is proposed to use an asymptotic approach which is especially relevant due to high number of pixels in a digital image. Hence, it follows from central limit theorem [11, theorem 11.2.5] that the log-LR $\Lambda^{\text{np}}(\mathbf{Z})$ satisfies, as $N \rightarrow \infty$:

$$\frac{\sum_{n=1}^{N-1} [\Lambda^{\text{np}}(\zeta_n)] - (N-1)m_i(b)}{\sqrt{(N-1)s_i^2(b)}} \rightsquigarrow \mathcal{N}(0, 1), \quad (10)$$

where \rightsquigarrow represents the convergence in distribution, and $m_i(b) = \mathbb{E}_i[\Lambda^{\text{np}}(\zeta_n)]$ and $s_i^2(b) = \text{Var}_i[\Lambda^{\text{np}}(\zeta_n)]$ respectively denotes the expectation and the variance of the log-LR $\Lambda^{\text{np}}(\zeta_n)$ under hypothesis \mathcal{H}_i , $i = \{0, 1\}$.

The log-likelihood ratio $\Lambda^{\text{np}}(\zeta_n)$ is a piecewise-defined function, see Figure 2, which can accurately be approximated using a Taylor expansion. However, the exact expression of $m_i(b)$ and $s_i^2(b)$ are simple but rather long and do not have a great interest in this paper. Thus, it is proposed to denote

$$m_0(b) = \int_{\mathbb{R}} p_b(\zeta) \Lambda^{\text{np}}(\zeta) d\zeta, \quad (11)$$

$$\text{and } s_0^2(b) = \int_{\mathbb{R}} p_b(\zeta) (\Lambda^{\text{np}}(\zeta) - m_0(b))^2 d\zeta.$$

the two first moment of log-LR $\Lambda^{\text{np}}(\zeta_n)$ under \mathcal{H}_0 which only depends on scale parameter b and can simply be analytically

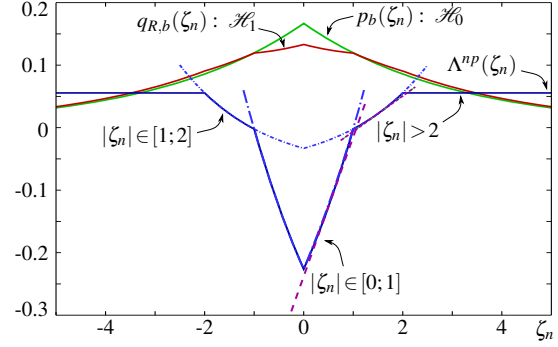


Fig. 2: Illustration of log-LR $\Lambda^{\text{np}}(\zeta_n)$ showing its piecewise definitions and their first order Taylor expansion.

calculated. The calculation of moments $m_1(b)$ and $s_1(b)$, under \mathcal{H}_1 , is similar to (11) and thus, omitted due to the lack of space.

From the central limit theorem (10) it is proposed to slightly modify the LR $\Lambda^{\text{np}}(\zeta_n)$ by defying:

$$\tilde{\Lambda}^{\text{np}}(\mathbf{Z}) = \frac{1}{\sqrt{N-1}} \sum_{n=1}^{N-1} \left[\frac{\Lambda^{\text{np}}(\zeta_n) - m_0(b)}{s_0(b)} \right], \quad (12)$$

so that under null hypothesis \mathcal{H}_0 it holds that $\tilde{\Lambda}^{\text{np}}(\mathbf{Z}) \rightsquigarrow \mathcal{N}(0, 1)$. The use of LR $\tilde{\Lambda}^{\text{np}}(\mathbf{Z})$ does not change the properties of LRT (9) up to the decision threshold τ_{α_0} and permits to simplify the expression of its parameters in the following Theorem 1.

Theorem 1. Assuming that model (2)-(3) holds and that scale parameter b are known, then, the decision threshold:

$$\hat{\tau}_{\alpha_0} = \Phi^{-1}(1 - \alpha_0), \quad (13)$$

where Φ^{-1} denotes the Gaussian standard quantile function (inverse cdf), asymptotically warrants that as $N \rightarrow \infty$ the LRT based on $\tilde{\Lambda}^{\text{np}}(\mathbf{Z})$ is in the class \mathcal{H}_{α_0} . For any $R \in [0, 1]$, choosing the decision threshold $\hat{\tau}_{\alpha_0}$ (13) the power $\beta_{R,b}^{\text{np}}$ associated with the LRT (8) is given by:

$$\beta_{R,b}^{\text{np}} = 1 - \Phi \left(\frac{s_0(b)}{s_1(b)} \hat{\tau}_{\alpha_0} - R \sqrt{N-1} \left(\frac{m_1(b) - m_0(b)}{s_1(b)} \right) \right), \quad (14)$$

where $m_i(b)$, and $s_i(b)$ are the two firsts moments of LR $\Lambda^{\text{np}}(\zeta_n)$ under hypothesis \mathcal{H}_i , $i = \{0, 1\}$ and Φ denotes the Gaussian standard cdf.

The proof of Theorem 1 is omitted due to lack of space.

It can be noted that the main advantage of using LR $\tilde{\Lambda}^{\text{np}}(\mathbf{Z})$, as defined in (12), is that the decision threshold given in (13) only depends on α_0 . Thus, $\hat{\tau}_{\alpha_0}$ remains the same for any inspected image and for any embedding rate R .

Additionally, Equation (14) provides an explicit expression of detection power of the most powerful LRT which thus, can be used as an optimal bound for any proposed test.

5. GENERALIZED LRT FOR UNKNOWN MEDIA

When inspecting an unknown medium, the proposed approach requires an estimation expectations vector $\theta = (\theta_1, \dots, \theta_N)^T$ to calculate ζ_n , see Equation (2). The problem of estimating pixels expectation in an open problem which have been widely studied in the literature and lies outside the scope of this paper. In the present paper, it is proposed to use two common methods for estimating pixels expectation. First the wavelet shrinkage method based on soft-thresholding of wavelet decomposition coefficients is used [12]:

$$\hat{\theta}_{\mathcal{W}} = \mathbf{W}^T \mathcal{F}(\mathbf{W}\mathbf{Z}), \quad (15)$$

where \mathbf{W} is a unitary matrix representing wavelet decomposition and \mathcal{F} is the soft-thresholding function. Second, because it has been successfully used for WS ste-ganalysis [1], a 2D linear filtering of image is used:

$$\hat{\theta}_{\mathcal{F}} = \mathcal{F}(\mathbf{Z}) = \mathbf{F} * \mathbf{Z}, \quad (16)$$

where \mathcal{F} represent the linear 2D filtering operation which consists in a convolution product $*$ between image \mathbf{Z} and filter matrix \mathbf{F} , usually of small size typically 3×3 . The consequent impact of detection performance are shown through numerical results in Figures 4.

The scale parameter b of Laplacian distribution has also to be estimated. According to definition of GLRT, see also definition of class \mathcal{H}_{α_0} , parameter b has to be estimated twice using maximum likelihood estimation under both hypothesis:

$$\Lambda^{\text{glr}}(\mathbf{Z}) = \log \left(\frac{\max_{\hat{b}_0 \in \mathbb{R}^+} \prod_{n=1}^{N-1} p_{\hat{b}_0}(\zeta_n)}{\max_{\hat{b}_1 \in \mathbb{R}^+} \prod_{n=1}^{N-1} q_{R, \hat{b}_1}(\zeta_n)} \right). \quad (17)$$

The maximum likelihood estimation (MLE) of parameter b under \mathcal{H}_1 does not have an explicit solution. Thus, in the present paper it is proposed to use the MLE of parameter b given, for medium \mathbf{Z} , under hypothesis \mathcal{H}_0 by:

$$\hat{\Lambda}^{\text{glr}}(\mathbf{Z}) = \sum_{n=1}^{N-1} \hat{\Lambda}^{\text{glr}}(\hat{\zeta}_n) = \sum_{n=1}^{N-1} \log \left(\frac{p_{\hat{b}_0}(\hat{\zeta}_n)}{q_{R, \hat{b}_0}(\hat{\zeta}_n)} \right), \quad (18)$$

where $\hat{\zeta}_n = (z_n - \hat{\theta}_{n+1}) - (z_n - \hat{\theta}_n)$ and $\hat{\theta}_n$ is the estimated n -th pixel expectation (15)-(16). A short calculation shows that the MLE \hat{b}_0 of b under hypothesis \mathcal{H}_0 is given, for each inspected image, by:

$$\hat{b}_0 = \frac{1}{N-1} \sum_{n=1}^{N-1} |\zeta_n|. \quad (19)$$

Moreover, in virtue of central limit theorem (10), a short algebra shows that the estimation \hat{b}_0 satisfies:

$$\hat{b}_0 \sim \mathcal{N} \left(b, \frac{b^2}{N-1} \right). \quad (20)$$

By using distribution of \hat{b}_0 (20), the two first moments of $\hat{\Lambda}^{\text{glr}}(\mathbf{Z})$ are given under hypothesis \mathcal{H}_0 , from the law of to-

tal expectation and the law of total variance, by:

$$\hat{m}_0(b) = \mathbb{E}_{\hat{b}_0} \left[\mathbb{E}_0 [\hat{\Lambda}^{\text{glr}}(\mathbf{Z}) | \hat{b}_0] \right], \quad (21)$$

$$\hat{s}_0^2(b) = \mathbb{E}_{\hat{b}_0} \left[\text{Var}_0 [\hat{\Lambda}^{\text{glr}}(\mathbf{Z}) | \hat{b}_0] \right] + \text{Var}_{\hat{b}_0} \left[\mathbb{E}_0 [\hat{\Lambda}^{\text{glr}}(\mathbf{Z}) | \hat{b}_0] \right]$$

where $\mathbb{E}_{\hat{b}_0}[\cdot]$ and $\text{Var}_{\hat{b}_0}[\cdot]$ denotes the expectation and variance with respect the random variable \hat{b}_0 . The calculation of moments $\hat{m}_1(b)$ and $\hat{s}_1(b)$, under hypothesis \mathcal{H}_1 , is similar to (21) and thus, omitted due to the lack of space.

As previously proposed in the case of the LRT (12), let us formally defines proposed test δ^{glr} as follows:

$$\delta^{\text{glr}}(\mathbf{Z}) = \begin{cases} \mathcal{H}_0 & \text{if } \frac{1}{\sqrt{N-1}} \sum_{n=1}^{N-1} \frac{\hat{\Lambda}^{\text{glr}}(\hat{\zeta}_n) - \hat{m}_0(b)}{\hat{s}_0(b)} \leq \hat{\tau}_{\alpha_0}^{\text{glr}}, \\ \mathcal{H}_1 & \text{if } \frac{1}{\sqrt{N-1}} \sum_{n=1}^{N-1} \frac{\hat{\Lambda}^{\text{glr}}(\hat{\zeta}_n) - \hat{m}_0(b)}{\hat{s}_0(b)} > \hat{\tau}_{\alpha_0}^{\text{glr}}. \end{cases} \quad (22)$$

The following Theorem 2 provides an analytic expression of proposed test $\delta^{\text{glr}}(\mathbf{Z})$ parameters.

Theorem 2. Assuming that estimation $\hat{\theta}$ of θ (15)-(16) satisfies model (3), then, the decision threshold:

$$\hat{\tau}_{\alpha_0}^{\text{glr}} = \Phi^{-1}(1 - \alpha_0) \quad (23)$$

asymptotically warrants that proposed test $\delta^{\text{glr}}(\mathbf{Z}) \in \mathcal{H}_{\alpha_0}$.

For any $R \in [0; 1]$, choosing the decision threshold $\hat{\tau}_{\alpha_0}^{\text{glr}}$ (23), the power $\beta_{R, \hat{b}_0}^{\text{glr}}$ associated with the test δ^{glr} (22) is given by

$$\hat{\beta}_{R, \hat{b}_0}^{\text{glr}} = 1 - \Phi \left(\frac{\hat{s}_0(b)}{\hat{s}_1(b)} \hat{\tau}_{\alpha_0}^{\text{glr}} - R\sqrt{N-1} \left(\frac{\hat{m}_1(b) - \hat{m}_0(b)}{\hat{s}_1(b)} \right) \right) \quad (24)$$

where $\hat{m}_i(b)$, and $\hat{s}_i(b)$ the two firsts moments of LR $\hat{\Lambda}^{\text{glr}}(\hat{\zeta}_n)$ under hypothesis \mathcal{H}_i , $i = \{0, 1\}$, see Equation (21).

The proof of Theorem 2 is omitted due to lack of space.

6. NUMERICAL RESULTS

To emphasis the relevance of proposed model and approach, a numerical simulation on a large database was performed. The BOSS contest database [13] made of 10000 images of size 512×512 was used. Figures 3a and 3b presents the numerical results witch permits a comparison between proposed GLRT and two state-of-the-art detectors, namely ALE [2] and Adjacent HCFCOM [3]. It can be noticed that proposed GLRT based on wavelet or 2D-filtering content estimation outperforms these two detectors, especially for low embedding rate R , see Figure 3b with $R = 0.25$.

This paper aims to design a test with analytically predictable performance. Hence, Figure 4 presents a comparison between empirical power of LR and GLR tests and their theoretical expressions, given by Equations (14) and (24). Results were obtained using a Monte Carlo simulation with 10000 realizations each with $N = 1024$ pixels following a Laplacian distribution with scale parameter $b = \{2; 4; 10\}$. Figure 4

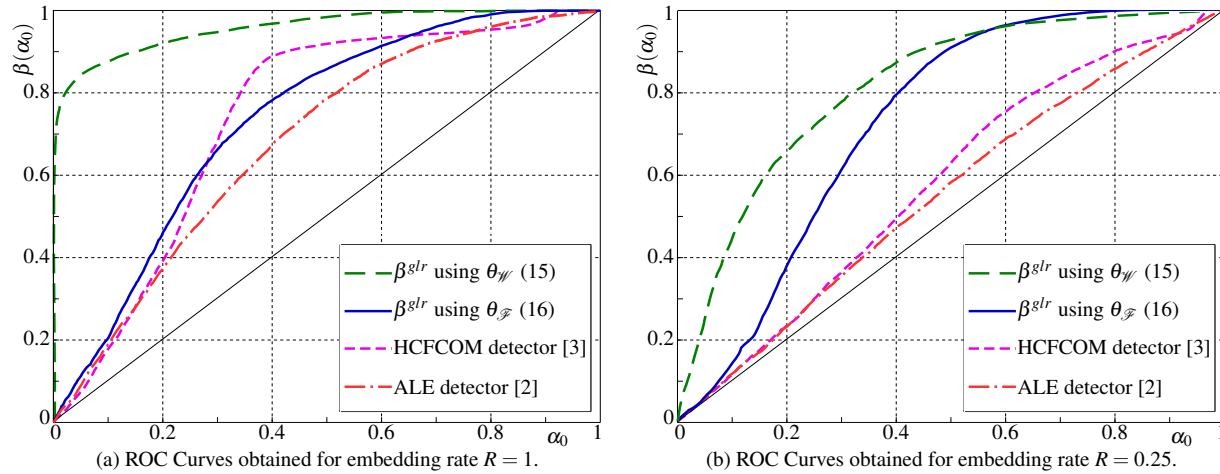


Fig. 3: Performance comparison between proposed test and detectors proposed in [2, 3] for BOSS contest database [13].

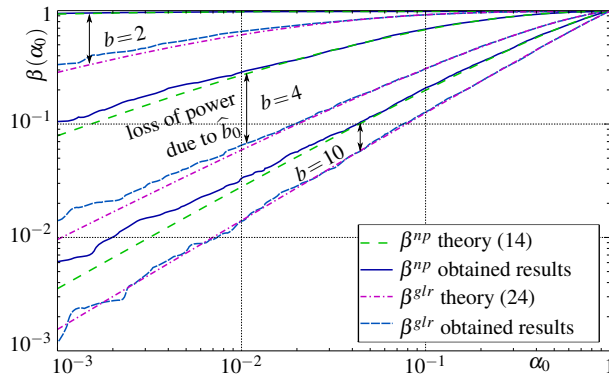


Fig. 4: Comparison between theoretical and empirical detection power as a function of false alarm probability α_0 ; simulated data with $N = 1024$ samples and $b = \{2.5; 5; 10\}$.

highlights that empirical detection power is very closed to the theoretically established expression. However, it should also be noted that even though ML estimation of scale parameter is unbiased and has a small variance (20), this variance highly impacts the detection power. Indeed the likelihood ratio is very sensitive to a small error on scale parameter.

7. CONCLUSION

This paper made a first step in the statistical detection LSB steganography. A methodology is proposed to avoiding dealing with nuisance parameter by using a statistical model of adjacent pixels difference. The main contributions are the three-fold. First, the most powerful LRT is presented and its statistical performance are analytically established; this provides an optimal bound on detection power for any test. Second, when none image parameters are known, a test based on GLRT is presented and its statistical performances are also established. Especially, the decision threshold that warrants a prescribed false-alarm probability is explicitly given. Finally, numerical simulation show that proposed test outperforms state-of-the-art detectors.

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