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ASYMPTOTICALLY OPTIMAL DETECTION OF LSB MATCHING DATA HIDING

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ABSTRACT

This paper proposes a novel method, based on hypothesis testing theory, to detect data hidden with the LSB matching. When all the image parameters, a test which asymptotically maximizes the detection power and guarantees a false-alarm probability, is presented and its statistical properties are analytically given in a closed-form. This provides an asymptotic upper-bound for the power of any detector for LSB matching. In practice the image parameters are unknown. A Generalized Likelihood Ratio Test (GLRT) is proposed and its statistical properties are also analytically established. Numerical results and comparisons with prior art detectors highlight the relevance of the proposed methodology.

***Index Terms*—** Hypothesis testing theory, Information forensics, Optimal detection, Nuisance parameters.

1. INTRODUCTION

Steganography concerns the transmission of a secret message buried in a host digital cover medium. With many tools available in the public domain, steganography have received increasing interest as it is easily available to anyone, for legitimate or malicious use. In an operational context, the detection of rather simple but most commonly found stegosystem remains crucial. While the detection of LSB replacement is possible with a high accuracy [1], the steganalysis of LSB matching remains much harder [1, 2, 3]. Therefore the detection of steganographic algorithms based on LSB matching remains important. The recently proposed steganalyzers dedicated to LSB matching can be roughly divided into two categories [2]. On the one hand, most of the latest detectors are based on supervised machine learning methods and use targeted [4, 5] or universal features [6, 7]. As in all applications of machine learning, a difficult problem is to choose an appropriate features set. On the other hand, it was proposed in [8] to exploit the image Histogram Characteristic Function (HCF). This led to an entire family of histogram-based detectors [9, 3]. In an practical situation, it is crucial to provide the statistical test with analytically predictable results to guarantee a false-alarm probability. The previously proposed LSB matching steganalyzers are very interesting and efficient, but their statistical properties remain analytically unknown.

In the present paper it is proposed to address the problem of LSB matching steganalysis by using hypothesis testing theory [10, 11, 12]. The contributions of this paper are the following: 1) Based on the Likelihood Ration Test (LRT), an Asymptotically Uniformly Most Powerful (AUMP) test, which maximizes the detection power whatever the hidden information might be, is proposed. 2) The statistical performance of proposed AUMP test is analytically established as the number of pixels grows to infinity, and 3) when the inspected image parameters are unknown, a GLRT is proposed based on a local linear model of pixels.

The paper is organized as follows. The problem of LSB matching steganalysis is stated in Section 2. The optimal LRT test and the proposed AUMP test are presented and studied in Section 3. Section 4 presents the proposed GLRT and studies establishes is statistical performance. Finally, Section 5 presents numerical results and simulations. Section 6 concludes the paper.

2. STEGANALYSIS PROBLEM STATEMENT.

Let the column vector $\mathbf{c} = (c_1, \dots, c_N)^T$ represents an uncompressed cover medium of N samples (a sound, an image, a video, etc). Each sample c_n belongs to $\mathcal{Z} = \{0; \dots ; 2^b - 1\}$ as it results from the quantization:

$$c_n = Q(y_n), \tag{1}$$

where $y_n \in \mathbb{R}^+$ denotes the recorded sample intensity and Q represents the uniform quantization with unit step (rounding of y_n). Each recorded sample value can be written as [11, 13]:

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

where θ_n is a deterministic parameter corresponding to the mathematical expectation of y_n (content of image) and ξ_n

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represents all the noise corrupting cover image. As described in [11, 13, 14], the ξ_n's can accurately be modeled as independent Gaussian random variables with variance σ_n^2 : $\xi_n \sim \mathcal{N}(0, \sigma_n^2)$. It thus follows from (1)-(2) that the probability mass function (pmf) of c_n is given by $P_{\theta_n} = (p_{\theta_n}[0], \dots, p_{\theta_n}[2^b - 1])$, with for all $k \in \mathcal{Z}$:

$$p_{\theta_n}[k] = \frac{1}{\sigma_n} \int_{k-\frac{1}{2}}^{k+\frac{1}{2}} \phi\left(\frac{u-\theta_n}{\sigma_n}\right) du \approx \frac{1}{\sigma_n} \phi\left(\frac{k-\theta_n}{\sigma_n}\right). \quad (3)$$

In this paper, ϕ denotes the standard Gaussian probability density function (pdf). This paper focus on digital media for which the noise variance is high, *i.e.* typically $\sigma_n > 1$, for which the detection of hidden information is the hardest. In this situation, calculations show that approximation (3) is very accurate [11].

To model the statistical impact of data hiding, the two following assumptions are usually admitted [1, 11] : 1) each cover sample has the same probability of being used to hide a secret bit and 2) each hidden bit m_l of the message $\mathbf{m} = (m_1, \dots, m_L)^T$ follows a binomial distribution $\mathcal{B}(1, 1/2)$.
Let the embedding rate R be defined as the number of hidden bits per sample: $R = L/N$. The LSB matching scheme consists in randomly incrementing or decrementing each sample value whose LSB differs from the bit to be inserted. Using the two previous assumptions, a short calculation shows that the pmf of c_n after insertion at rate R is given by $Q_{R,\theta_n} = \{q_{R,\theta_n}[0], \cdots, q_{R,\theta_n}[2^b - 1]\}$ where, for all $k \in \mathcal{Z}$:

$$q_{R,\theta_n}[k] = \frac{R}{4}\left(p_{\theta_n}[k-1] + p_{\theta_n}[k+1]\right) + \left(1 - \frac{R}{2}\right) p_{\theta_n}[k]. \quad (4)$$

When analyzing an unknown image $\mathbf{z} = (z_1, \dots, z_N)^T$, whose expectation is denoted $\boldsymbol{\theta} = (\theta_1, \dots, \theta_N)^T \in \Theta \subset \mathbb{R}^N$, it is aimed at deciding between the following hypotheses:

$$\begin{aligned} \mathcal{H}_0 &= \left\{ z_n \sim P_{\theta_n}, \forall n \in \{1, \dots, N\}, \forall \boldsymbol{\theta} \in \Theta \right\} \\ \mathcal{H}_1 &= \left\{ z_n \sim Q_{\theta_n}^R, \forall n \in \{1, \dots, N\}, \forall \boldsymbol{\theta} \in \Theta, \forall R \in (0, 1] \right\} \end{aligned} \quad (5)$$

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 in [15]). Let

$$\mathcal{K}_{\alpha_0} = \{\delta : \sup_{\boldsymbol{\theta} \in \Theta} \mathbb{P}_0[\delta(\mathbf{z}) = \mathcal{H}_1] \le \alpha_0\},$$

be the class of tests whose false alarm probability are upper-bounded by α_0. Here, $\mathbb{P}_i(A)$ stands for the probability of the event A under hypothesis $\mathcal{H}_i$, $i = \{0; 1\}$ and the supremum over Θ has to be understood as whatever the expectation of image pixels might be. For a test $\delta \in \mathcal{K}_{\alpha_0}$, it is obviously desirable to maximize the power function β_δ defined as the correct detection probability:

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

The first difficulty of testing problem (5) is that the rate R is unknown which makes $\mathcal{H}_1$ composite [11]. In addition it is crucial to deal with nuisance parameter $\boldsymbol{\theta}$ which in unknown in practice and may prevent hidden data detection [12, 16].

3. LRT AND THE PROPOSED AUMP TEST.

In virtue of Neyman-Pearson lemma, see [15, theorem 3.2.1], the most powerful (MP) test over the class $\mathcal{K}_{\alpha_0}$ is the likelihood ratio test (LRT). The definition of hypotheses (3)-(4) immediately permits the writing of the log-LR as:

$$\Lambda_R(z_n) = \log \left[\frac{R}{4} \frac{p_{\theta_n}[z_n - 1] + p_{\theta_n}[z_n + 1]}{p_{\theta_n}[z_n]} + \left(1 - \frac{R}{2}\right) \right].$$

By using the approximation (3), a short algebra gives:

$$\begin{aligned} &\frac{1}{2} \frac{p_{\theta_n}[z_n - 1] + p_{\theta_n}[z_n + 1]}{p_{\theta_n}[z_n]} = \\ &\qquad \frac{1}{2} \exp\left(-\frac{1}{2\sigma_n^2}\right) \left[\exp\left(\frac{\theta_n - z_n}{\sigma_n^2}\right) + \exp\left(\frac{z_n - \theta_n}{\sigma_n^2}\right) \right]. \end{aligned} \quad (6)$$

It is obvious from Equation (6) that

$$\frac{1}{2} \frac{p_{\theta_n}[z_n - 1] + p_{\theta_n}[z_n + 1]}{p_{\theta_n}[z_n]} - 1 \to 0,$$

as σ_n^{-1} tends to 0. Hence, the Taylor series expansion of $\log(1 + x)$ and $\exp(x)$ permits the writing of:

$$\Lambda_R(z_n) = \frac{R}{4\sigma_n^4} \left((z_n - \theta_n)^2 - \sigma_n^2 + \frac{1}{4} \right) - \frac{R^2}{32\sigma_n^4} + o\left(\sigma_n^{-4}\right). \quad (7)$$

This expression (7) is used to design the proposed AUMP test.

From the expression (7), it is obvious that when $\boldsymbol{\theta}$ is known, the log-LR Λ_R only depends on the observation through the term:

$$\frac{(z_n - \theta_n)^2}{\sigma_n^4}.$$

Hence, it is proposed to base the proposed test on the following quantity:

$$\Lambda_{\text{aump}}(z_n) = \frac{(z_n - \theta_n)^2 - 1/12}{\sigma_n^4} - \frac{1}{\sigma_n^2}. \quad (8)$$

The choice to replace LR $\Lambda_R(z_n)$ in the proposed test the by the quantity $\Lambda_{\text{aump}}(z_n)$ is motivated by the following arguments. First, it can be noted that $\Lambda_{\text{aump}}(z_n)$ differs from the LR $\Lambda_R(z_n)$ only by an additive constant and a multiplicative constant, which do not change the performance of the ensuing test, as formalized in Theorem 2. Second, by using the results [18], the statistical properties of $\Lambda_{\text{aump}}(z_n)$ can be calculated easily. Last but not least, the dependance with embedding rate R has been removed from Equation (8); this quantity can thus be calculated when R is unknown.

Let the quantities $\bar{\sigma}^4$ and ϱ, which roughly speaking respectively represents the "mean squared variance" of pixels and the "Insertion-to-Noise Ratio", be defined as:

$$\bar{\sigma}^{-4} \stackrel{\text{def.}}{=} N^{-1} \sum_{n=1}^{N} \sigma_n^{-4} \quad \text{and} \quad \varrho \stackrel{\text{def.}}{=} \frac{R}{\bar{\sigma}^2 \sqrt{8}}. \quad (9)$$

The test proposed in this paper is formally defined by:

$$\delta_{\text{aump}} = \begin{cases} \mathcal{H}_0 & \text{if} \quad \Lambda_{\text{aump}}(\mathbf{Z}) \leq \tau_{\alpha_0} \\ \mathcal{H}_1 & \text{if} \quad \Lambda_{\text{aump}}(\mathbf{Z}) > \tau_{\alpha_0}, \end{cases} \tag{10}$$

$$\text{where } \Lambda_{\text{aump}}(\mathbf{Z}) = \frac{\bar{\sigma}^2}{\sqrt{2N}} \sum_{n=1}^{N} \Lambda_{\text{aump}}(z_n). \tag{11}$$

The properties of the proposed test δ_{aump} (10) are established by the following Theorem 1.

Theorem 1. *For any $\alpha_0 \in (0,1)$, assuming that the parameter $\boldsymbol{\theta}$ is known, the decision threshold τ_{α_0} given by:*

$$\tau_{\alpha_0} = \Phi^{-1}(1-\alpha_0) \tag{12}$$

where $\Phi^{-1}(\cdot)$ is the Gaussian inverse cumulative distribution, asymptotically guarantees that the test δ_{aump} (10) is in $\mathcal{K}_{\alpha_0}$. Using the threshold τ_{α_0} given in (12), the power function $\beta_{\text{aump}}(\varrho)$ of the test δ_{aump} (10) is asymptotically given by:

$$\beta_{\text{aump}}(\varrho) = 1 - \Phi\left(\Phi^{-1}(1-\alpha_0) - \sqrt{N}\varrho\right). \tag{13}$$

Proof. proof of Theorem 1 is omitted due to space limit. □

The Theorem 1 highlights two main interests of the proposed test δ_{aump} (10). First, the decision threshold given by (12) only depends on the prescribed false-alarm probability α_0. Hence, using the proposed test, it is straightforward to guarantee any given false-alarm probabability. Second, the power function given in Equation (13) provides a simple expression of proposed test detection power, as σ_n^{-1} tends to 0. This establishes an upper bound for the detection power of any detector and provides a relation between image parameters and detection power.

Before dealing with the optimal properties of the proposed test, the Asymptotically Uniformly Most Powerful (AUMP) property is recalled hereby [15, Definition 13.3.2]:

Definition 1. *For testing the hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$ (5), a test $\delta^\star$ is AUMP in the class $\mathcal{K}_{\alpha_0}^\infty$ defined as:*

$$\mathcal{K}_{\alpha_0}^\infty = \left\{ \delta : \limsup_{N\to\infty} \sup_{\boldsymbol{\theta}\in\Theta} \mathbb{P}_0[\delta(\mathbf{Z}) = \mathcal{H}_1] \leq \alpha_0 \right\}.$$

if $\delta^\star \in \mathcal{K}_{\alpha_0}^\infty$ and for any other test $\delta \in \mathcal{K}_{\alpha_0}^\infty$ it holds that $\forall R \in (0;1]$, $\forall \theta \in \Theta$, $\limsup_{N\to\infty} \beta_\delta - \beta_{\delta^\star} \leq 0$.

In other words, a AUMP test asymptotically guarantees a fixed false-alarm probability and maximizes the detection power, whatever the expectation of image pixels and the embedding rate might be. The following Theorem 2 establishes the optimality of the proposed statistical test δ_{aump} (10).

Theorem 2. *For any given probability of false alarm $\alpha_0 \in (0,1)$, assuming that $\boldsymbol{\theta}$ is known and that $\sigma_n^{-1} \to 0$ then it holds that δ_{aump} is AUMP is the class $\mathcal{K}_{\alpha_0}^\infty$ provided that the decision threshold is chosen as in Equation (12).*

Proof. proof of Theorem 2 is omitted due to space limit. □

The Theorem 2 formally states that Equation (13) provides an upper bound for the detection power of any detector.

4. LOCAL LINEAR MODEL AND PROPOSED GLRT.

In practice, neither the expectation θ_n nor the variance σ_n^2 of pixels is known. In such a situation, a usual solution is to replace the unknown values by their Maximum Likelihood Estimation (MLE), denoted $\widehat{\theta}_n$ and $\widehat{\sigma}_n^2$ respectively. This leads to design the well-known Generalized Likelihood Ratio Test (GLRT). To this end, $\mathbf{Z}$ is split in a set of K non-overlapping blocks of L pixels, with $N \approx KL$. Let us define, for all $k \in \{1,\ldots,K\}$, the k-th block $\mathbf{z}_k = (\mathbf{z}_{k,1},\ldots,\mathbf{z}_{k,L})^T$ as:

$$\mathbf{z}_k = Q(\mathbf{y}_k)\,,\, \mathbf{y}_k = \boldsymbol{\theta}_k + \boldsymbol{\xi}_k \sim \mathcal{N}(\boldsymbol{\theta}_k, \sigma_k^2 \mathbf{I}_L), \tag{14}$$

where the operation of uniform quantization Q is applied on each sample individually, σ_k^2 is the pixels variance assumed constant on each block and $\mathbf{I}_L$ is the identity matrix of size $L \times L$. In the present paper, the following linear parametric model [11, 17] is used:

$$\boldsymbol{\theta}_k = \mathbf{H}\mathbf{x}_k, \tag{15}$$

where $\mathbf{H}$ is a known full rank matrix of size $L \times p$, with $p < L$, and $\mathbf{x}_k \in \mathbb{R}^p$ is the nuisance parameter describing $\boldsymbol{\theta}_k$.
The hypothesis testing theory is well developed for models such as (15). In fact, the theory of invariance [15, Chap. 6] allows the rejection of nuisance parameters $\boldsymbol{\theta}_k$.

It follows from model (14) - (15) that the MLE of $\boldsymbol{\theta}_k$ and σ_k, respectively denoted $\widehat{\boldsymbol{\theta}}_k$ and $\widehat{\sigma}_k$, are given by:

$$\widehat{\boldsymbol{\theta}}_k = \mathbf{H}(\mathbf{H}^T\mathbf{H})^{-1}\mathbf{H}^T\mathbf{z}_k \text{ and } \widehat{\sigma}_k^2 = \frac{\left\|\mathbf{z}_k - \widehat{\boldsymbol{\theta}}_k\right\|_2^2}{L-p} - \frac{1}{12}.$$

Theory of invariance thus permits us to reject nuisance parameters, and from (6), to write the proposed GLR calculated on k-th block as:

$$\Lambda_{\text{glr}}(\mathbf{z}_k) = \sum_{l=1}^{L} \left[\frac{(z_{k,l} - \widehat{\theta}_{k,l})^2}{\widehat{\sigma}_k^4} \right] - (L-p)\frac{1/12 + \widehat{\sigma}_k^2}{\widehat{\sigma}_k^4}.$$

With these definitions, the proposed GLRT is given as:

$$\delta_{\text{glr}}(\mathbf{Z}) = \begin{cases} \mathcal{H}_0 & \text{if} \quad \Lambda_{\text{glr}}(\mathbf{Z}) \leq \tau_{\alpha_0} \\ \mathcal{H}_1 & \text{if} \quad \Lambda_{\text{glr}}(\mathbf{Z}) > \tau_{\alpha_0}, \end{cases} \tag{16}$$

$$\text{with } \Lambda_{\text{glr}}(\mathbf{Z}) = \frac{\bar{\sigma}^2}{\sqrt{2K(L-p)}} \sum_{k=1}^{K} \Lambda_{\text{glr}}(\mathbf{z}_k). \tag{17}$$

The following Theorem 3 establishes the power of the proposed GLRT.

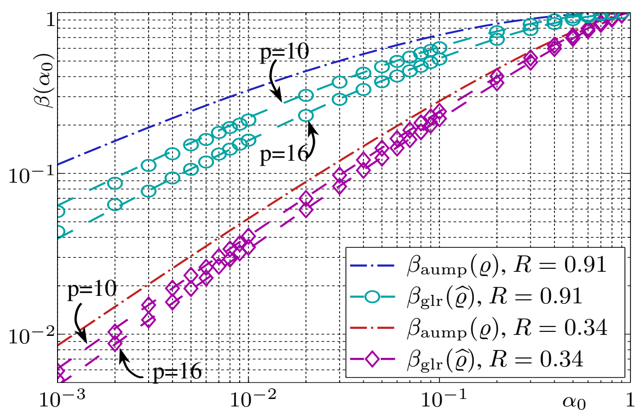

Fig. 1. Power of proposed test $\beta_{\mathrm{glr}}(\varrho)$ as a function of false-alarm probability α_0 (ROC curve).

Theorem 3. *For any $\alpha_0 \in (0,1)$, assuming that the model (14) and (15) holds, the decision threshold $\widehat{\tau}_{\alpha_0}$ given by:*

$$\widehat{\tau}_{\alpha_0} = \Phi^{-1}(1-\alpha_0) \tag{18}$$

asymptotically guarantees that the test δ_{glr} (16) is in $\mathcal{K}_{\alpha_0}$. Under the same conditions, for any $\alpha_0 \in (0,1)$, the power function $\beta_{\mathrm{glr}}(\varrho)$ of the test δ_{glr} (16) is given by :

$$\beta_{\mathrm{glr}}(\varrho) = 1 - \Phi\left(\Phi^{-1}(1-\alpha_0) - \sqrt{K(L-p)}\varrho\right). \tag{19}$$

Proof. proof of Theorem 3 is omitted due to space limit. □

As discussed in [19, 20], the estimation of pixels expectation and variance, even locally, is a very difficult problem. In this paper, is to propose to use an adaptive linear model: the p vectors of matrix $\mathbf{H}$ are adapted to each block $\mathbf{z}_k$, see [21, 22]. For the numerical experimentations, a two-dimensional Discrete Cosine Transform (2D-DCT) was used [23]. The components matrix of $\mathbf{H}$ were chosen by selecting the p most important absolute value of 2D-DCT coefficients.

5. NUMERICAL RESULTS AND COMPARISONS.

To verify that the proposed test δ_{glr} (16) performs as established in Theorem 3, a numerical simulation was performed on simulated data. The Monte-Carlo simulation was repeated $5 \cdot 10^4$ times by generating $K = 200$ blocks of $L = 32$ pixels which follow the linear parametric model (14) - (15) with $\sigma_n = 3.78$. Two different matrices $\mathbf{H}$, with $p = 10$ and $p = 16$ parameters, and two different embedding rates, $R = 0.91$ and $R = 0.34$, are used. Figure 1 offers a comparison between theoretical and empirical detection power as a function of prescribed false-alarm probability α_0. Figure 1 shows that empirical and theoretical results are almost the same which emphasizes that the proposed test permits us to establish the statistical performance of proposed test.

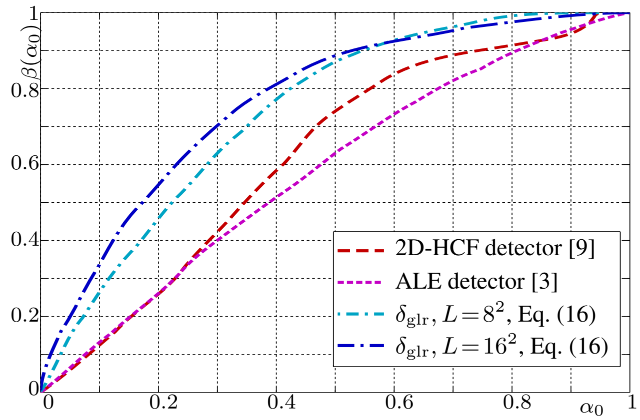

Fig. 2. Numerical comparisons of detectors performance using BOSS database [24] with rate $R = 0.5$.

To compare the proposed test with prior-art detector, two recent histogram-based detectors, namely the ALE (amplitude of local extrema [3]) and the 2D-HCF (adjacency Histogram Characteristic Function [9]) detector, are used. It should be noted that the comparison with blind detectors that rely on supervised leaning approach is difficult to the well-known cover-source mismatch problem [24] which makes hardly possible a meaningful comparison.Two different parametrizations of proposed GLR test Λ_{glr} (17) are presented in Figure 2; using the 2D-DCT on blocks of size $L = 8 \times 8$ pixels with $p = 8$ parameters and using blocks of size $L = 16 \times 16$ pixels while keeping $p = 16$ coefficients.
Figure 2 shows the results obtained using an embedding rate $R = 0.5$ with the 9 074 images from the Break Our Steganographic System (BOSS) contest [24]. Note that the version 0.92 of this database is used because later versions contain artifacts (due to improperly implemented lens distortion correction) which may skew the results.
The results presented in Figure 2 obviously show that the two proposed implementation of the GLRT achieve a better detection power for any prescribed false-alarm probability.

6. CONCLUSION.

The paper cast the detection of LSB matching steganalysis within the framework of hypothesis testing theory. The main contribution is twofold. First, an AUMP test, which asymptotically maximizes the detection power whatever the hidden data embedding rate might be, is presented. The statistical properties of the AUMP test is analytically calculated. This provides an upper bound for the detection power of any detector. Second, when inspected image parameters are unknown, a GLRT is prensed and its performance are also analytically established. The relevance of the proposed approach is emphasized through numerical experiments and comparison with prior-art detectors.

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