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Information hiding with maximum likelihood detector for correlated signals

Sayed Mohammad Ebrahim Sahraeian [a], Mohammad Ali Akhaee [b,*], Bulent Sankur [c], Farokh Marvasti [d]

[a] Department of Electrical Engineering, University of California at Berkeley, CA 94720-3102, USA
[b] School of Electrical and Computer Engineering, College of Engineering, University of Tehran, Tehran, Iran
[c] Electrical and Electronic Engineering Department, Bogazici University, Bebek, 34342, Istanbul, Turkey
[d] Advanced Communication Research Institute (ACRI), Department of Electrical Engineering, Sharif University of Technology, Tehran, Iran

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ABSTRACT

In this paper, a new scaling based information hiding approach with high robustness against noise and gain attack is presented. The host signal is assumed to be stationary Gaussian with first-order autoregressive model. For data embedding, the host signal is divided into two parts, and just one patch is manipulated while the other one is kept unchanged for parameter estimation. A maximum likelihood (ML) decoder is proposed which uses the ratio of samples for decoding the watermarked data. Due to the decorrelating property of the proposed decoder, it is very efficient for watermarking highly correlated signals for which the decoding process is not straightforward. By calculating the distribution of the decision variable, the performance of the decoder is analytically studied. To verify the validity of the proposed algorithm, it is applied to artificial Gaussian autoregressive signals. Simulation results for highly correlated host signals confirm the robustness of our decoder.

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1. Introduction

Digital watermarking embeds information within a digital work so that the inserted data becomes part of its medium. This technique serves various purposes such as intellectual right protection, broadcast monitoring, data authentication, data indexing, and metadata insertion [1–4]. A digital watermarking system should successfully satisfy trade-offs between conflicting requirements of perceptual transparency, data capacity and robustness against attacks [5]. There exists a trade-off in satisfying these requirements. Depending on the application, the importance of each requirement varies. For example, for secret communication purposes, noise immunity and data rate are more important, while for data authentication, imperceptibly and robustness are more significant.

While increasing the strength of the watermark obviously provides higher resistance against attacks, more intelligent designs select image features that are relatively more immune. This has led to a number of algorithms that make watermark insertion dependent upon image content. This principle is implemented widely in multiplicative watermarking [6] and recently in a scaling-based [7] method. To effectively hide the information, these approaches often employ various transform domains such as Discrete Cosine Transform (DCT), Discrete Fourier Transform (DFT), and Discrete Wavelet Transform (DWT) [8–10], which concentrate the energy of the host signal in fewer components. Since correlation detection is suboptimal for multiplicative watermarking in the transform domain, several alternative optimum and locally optimum decoders have been proposed [6,11–16]. Cheng and Huang [11] proposed a robust optimum detector for the multiplicative rule in the DCT, DWT and DFT domains. In their algorithm, they modeled the distribution of high frequency coefficients of DCT and DWT as Generalized Gaussian while they assumed the magnitude of DFT coefficients to have Weibull distribution.

In most current approaches [6–8,12,14–16], the transform coefficients are assumed to be i.i.d. (independent identically distributed) for convenience while this is not necessarily true in all environments. In fact there are steganalysis systems that explicitly use the dependency of DCT and DWT coefficients at inter-block level or at intra-block level [17,18]. These authors model the dependence of transform coefficients with Markov chains. Furthermore, there are several studies that exploit the correlation of discrete trigonometric transform (DTT) coefficients for data compression [19,20,22]. For instance, the variance spectrum of the

* Corresponding author.
E-mail addresses: msahraeian@berkeley.edu (S.M.E. Sahraeian), akhaee@ut.ac.ir (M.A. Akhaee), bulent.sankur@boun.edu.tr (B. Sankur), marvasti@sharif.edu (F. Marvasti).

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DCT coefficients in sub-blocks of images is characterized with an autoregressive (AR) model in [20], or the 2-D block spectrum of natural images is estimated by 1-D AR model [21]. Recently, Hsu and Liu [22] showed that AR modeling can be considered for temporal/spectral envelope of DTT coefficients.

This paper brings two new contributions to the watermarking methodologies. First, we develop a blind method that is robust to local gain attacks, that is spatial modulation. If the watermarked samples are subjected to modifications with spatially varying gain, it is desirable that the data hiding scheme preserve its watermark after this attack. The proposed method to this effect is a generalization of the data hiding scheme [7], the multi-bit scaling-based method, to a blind scheme. The method in [7] assumes the existence of a side information channel, but in practice it may be difficult to guarantee any such secure channel. Second, our method does not assume the cover signal samples to be i.i.d or uncorrelated. We assume autoregressive model of order one (AR(1)) to represent the host signal, not only because it is a common model for images, but it also leads to a closed form solution in our watermarking system. Similar to the patchwork approach [23], we separate the host signal into two subsets. One of them is left intact and serves for parameter estimation at the decoder site. The terms of the other subset are watermarked with the so-called scaling-based watermarking, which uses slight amplification or attenuations depending on the watermark bit. The strength of the algorithm comes from the fact that it is the ratio of samples that carry the watermark information instead of sample values themselves. This makes the algorithm not only suitable for highly correlated signals but also invariant to gain attack. The method is studied analytically using exact derivations to the extent possible, and approximations are introduced when analysis becomes intractable.

The rest of the paper is organized as follows: Statistical models of the signals occurring in the embedding and decoding stages are presented in Section 2. In Section 3, the ratio-based watermarking method is introduced. Performance analysis of the proposed method is given in Section 4. Section 5 contains simulation results to investigate the robustness of the proposed approach against AWGN attack and performance comparisons vis-a-vis other watermarking techniques. Finally, Section 6 concludes the paper.

2. Signal modeling

In this section, we show certain statistical properties of the carrier signal relevant for our watermarking algorithm. We assume that the cover signal is first-order Gauss–Markov signal, it is highly correlated, but it has low coefficient of variation. For example, the approximation band of the wavelet decomposed images has this property as discussed in Appendix A, hence the signal model is not restrictive. We can obtain a closed form solution for this signal model, but otherwise our watermarking algorithm applies to other signals as well. However for the other signal models a close form decoder may not exist. It is worth mentioning that we assume zig–zag scanning in ordering the image coefficients throughout the paper.

Let, $\mathbf{u}$ be this Gauss–Markov host sequence with mean μ, variance σ^2, and correlation coefficient ρ. The N samples $u_1, u_2, \dots, u_N$ of this parent sequence are split into two child sequences $\mathbf{x}$ and $\mathbf{y}$ consisting of the odd and even indexed terms, respectively: $x_i = u_{2i-1}$, $y_i = u_{2i}$, $i = 1, 2, \dots, \frac{N}{2}$. These $\mathbf{x}$ and $\mathbf{y}$ are also Gauss–Markov subsequences with means and variances identical to those of their parent, that is, with $x = \mathcal{N}(\mu_x, \sigma_x^2)$ and $y = \mathcal{N}(\mu_y, \sigma_y^2)$. Their auto-correlation coefficients are ρ^2 and their cross-correlation coefficient is ρ.

The carrier signal, $\mathbf{z}$, is another sequence formed as the termwise ratio of the two subsequences. The ratio sequence, as discussed in Section 3.2, will be used to build our optimum watermarking decoder.

We construct the ratio sequence $\mathbf{z}$ as follows:

$$z_i = \frac{x_i}{y_i} = \frac{u_{2i-1}}{u_{2i}}, \quad i = 1, \dots, \frac{N}{2}. \tag{1}$$

The probability density function of z for $\mu_y \neq 0$ is given as [25]:

$$f(z) = \frac{b(z)d(z)}{\sqrt{2\pi}\sigma_x\sigma_y a^3(z)}\left[2\Phi\left\{\frac{b(z)}{ra(z)}\right\} - 1\right] + \frac{re^{-c/2r^2}}{\pi\sigma_x\sigma_y a^2(z)} \tag{2}$$

where,

$$\begin{aligned}
a(z) &= \sqrt{\frac{z^2}{\sigma_x^2} - \frac{2\rho z}{\sigma_x\sigma_y} + \frac{1}{\sigma_y^2}}, \\
b(z) &= \frac{\mu_x z}{\sigma_x^2} - \frac{\rho(\mu_x + \mu_y z)}{\sigma_x\sigma_y} + \frac{\mu_y}{\sigma_y^2}, \\
c &= \frac{\mu_x^2}{\sigma_x^2} - \frac{2\rho\mu_x\mu_y}{\sigma_x\sigma_y} + \frac{\mu_y^2}{\sigma_y^2}, \\
d(z) &= \exp\left\{\frac{b^2(z) - ca^2(z)}{2r^2a^2(z)}\right\},
\end{aligned}$$

$r = 1 - \rho^2$, and $\Phi(t) = \int_{-\infty}^{t} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}r^2} dr$. In the special case of zero-mean variates, that is for $\mu_x = \mu_y = 0$, the distribution becomes Cauchy [24].

As we will see here, for the case of non zero μ_x and μ_y, and $\sigma_y \ll \mu_y$, $\sigma_x \ll \mu_x$, the distribution of $z = \frac{x}{y}$ can be well approximated by a Gaussian distribution. As shown in Appendix A, these small variance-to-mean conditions occur easily in the approximation bands of the wavelet decomposition of images. The parameters μ_z and σ_z^2 of the Gaussian approximation can be computed as follows. If we define $\bar{x} = x - \mu_x$, $\bar{y} = y - \mu_y$, and $\bar{z} = z - \mu_z$, we have:

$$\begin{aligned}
\mu_z + \bar{z} &= \frac{\mu_x + \bar{x}}{\mu_y + \bar{y}} = \frac{\mu_x(1 + \frac{\bar{x}}{\mu_x})}{\mu_y(1 + \frac{\bar{y}}{\mu_y})} \simeq \frac{\mu_x}{\mu_y}\left(1 + \frac{\bar{x}}{\mu_x}\right)\left(1 - \frac{\bar{y}}{\mu_y}\right) \\
&\simeq \frac{\mu_x}{\mu_y}\left(1 + \frac{\bar{x}}{\mu_x} - \frac{\bar{y}}{\mu_y} - \frac{\bar{x}\bar{y}}{\mu_x\mu_y}\right).
\end{aligned} \tag{3}$$

Taking the expectation of both sides of (3) and considering the fact that As $E(\bar{x}) = E(\bar{y}) = E(\bar{z}) = 0$, and $E(\bar{x}\bar{y}) = E((x - \mu_x)(y - \mu_y)) = \rho\sigma_x\sigma_y$, we have:

$$\mu_z = \frac{\mu_x}{\mu_y} \cdot E\left(1 + \frac{\bar{x}}{\mu_x} - \frac{\bar{y}}{\mu_y} - \frac{\bar{x}\bar{y}}{\mu_x\mu_y}\right) = \frac{\mu_x}{\mu_y} - \frac{\rho\sigma_x\sigma_y}{\mu_y^2} \tag{4}$$

Subtracting (3) from (4), we have:

$$\bar{z} = \frac{\mu_x}{\mu_y}\left(\frac{\bar{x}}{\mu_x} - \frac{\bar{y}}{\mu_y} - \frac{\bar{x}\bar{y}}{\mu_x\mu_y}\right) + \frac{\rho\sigma_x\sigma_y}{\mu_y^2} \tag{5}$$

Thus:

$$\begin{aligned}
\sigma_z^2 = E(\bar{z}^2) = E\Bigg[&\left(\frac{\bar{x}}{\mu_y}\right)^2 + \left(\frac{\mu_x\bar{y}}{\mu_y^2}\right)^2 + \left(\frac{\bar{x}\bar{y}}{\mu_y^2}\right)^2 \\
&+ \frac{\rho^2\sigma_x^2\sigma_y^2}{\mu_y^4} - 2\frac{\mu_x\bar{x}\bar{y}}{\mu_y^3} - 2\frac{\bar{x}^2\bar{y}}{\mu_y^3} + 2\frac{\mu_x\rho\sigma_x\sigma_y\bar{x}}{\mu_y^3} \\
&+ 2\frac{\mu_x\bar{x}\bar{y}^2}{\mu_y^4} - 2\frac{\mu_x\bar{y}\sigma_x\sigma_y}{\mu_y^4} - 2\frac{\rho\sigma_x\sigma_y\bar{x}\bar{y}}{\mu_y^4}\Bigg]
\end{aligned} \tag{6}$$

Now, to compute $E(\bar{x}^2\bar{y})$ consider that we write $\bar{y}$ as $\bar{y} = r_1\bar{x} + r_2$ where r_1 represents the correlated part of $\bar{y}$ and r_2 represents the

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