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Robustness improvement of known-host-state data-hiding using host statistics ☆

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Abstract

In this paper we considered the problem of performance improvement of known-host-state (quantization-based) watermarking methods undergo additive white Gaussian noise (AWGN) and uniform noise attacks. We question the optimality of uniform high rate quantizer based design of dither modulation and distortion compensate dither modulation methods from their robustness to these attacks point of view in terms of bit error rate probability. Motivated by superior performance of uniform deadzone quantizer over the uniform one in lossy source coding, we propose to replace the latter one by a former one designed according to the statistics of the host data. Based on suggested modifications we obtained analytical expressions for bit error rate probability analysis of quantization-based watermarking methods in AWGN and uniform noise channels. Experimental results of computer simulations demonstrated performance enhancement of known-host-state watermarking techniques in comparison to the classically elaborated schemes at negative watermark-to-noise ratios.

Keywords: Information hiding; Known-host-state watermarking; Quantization-based watermarking; High rate quantization; Uniform quantizer; Uniform deadzone quantizer; Bit error rate probability

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1. Introduction

Digital data-hiding is targeting at reliable communications of information through some kind of media. Therefore, one of possible criteria for the comparison of different data hiding technologies is the analysis of their information-theoretic performance limits [1,2].

Another criterion based on the consideration of a data hiding systems from the point of view of practical communications was recently proposed by [3] where the analysis is performed using bit error rate probability. The obtained results demonstrate the behavior of some known-host-state and known-host-statistics methods under certain channel distortions (additive white Gaussian noise (AWGN) attack and uniform noise attack). They also allow to conclude that for high watermark-to-noise ratios quantization-based methods outperform spread-spectrum based ones under assumption of uniform host pdf corresponding to large host variance while at low watermark-to-noise regime the situation is the opposite one.

The performed analysis is based on the assumption inspired by source coding that in case of high rate quantization uniform quantizer is optimal and quantization noise is independent from the host signal [4]. Several investigations have been performed targeting at establishing the possible ways of uniform quantizer performance improvement for real images in the transform domain when Laplacian or generalized Gaussian (GG) pdf are used as a stochastic model [5]. Among other solutions, one consists in preservation of the quantizer uniformity everywhere but not in the vicinity of zero where the bin width (the width of the deadzone) is larger than the width of all other bins. This simple modification leads to the superiority of the rate-distortion characteristics of this uniform deadzone quantizer (UDQ) for independent identically distributed (i.i.d.) Laplacian and GG data versus uniform one.

Motivated by this promising result we formulate the goal of this paper to answer the following question: is it possible to achieve better performance for dither modulation (DM) and DC-DM designed based on the UDQ in terms of bit error rate probability in AWGN and uniform noise channels?

The paper is organized as follows. In Section 2 we present an overview of known-host-state data-hiding. Section 3 contains bit error rate probability bounds for the DM and DC-DM designed using UDQ. In Section 4 bench-marking results for the deadzone-based DM and DC-DM are presented versus performance of the classical schemes. Finally, Section 5 concludes the paper.

Notations. We use capital letters to denote scalar random variables X and regular letters x to designate the realizations of scalar random variables. We use $X \sim f_X(x)$ or simply $X \sim f(x)$ to indicate that a continuous random variable X is distributed according to $f_X(x)$. The variance of X is denoted by σ_X^2. The set of integers is designated by $\mathbb{Z}$.

2. Known-host-state data-hiding

2.1. Dither modulation

Firstly, introduced in [6], dither modulation (DM) (Fig. 2a) refers to the embedding of the binary value b (a generalization to M-ary DM is possible but this aspect is outside of the scope of this paper) by quantizing the host image using one of two uniform quantizers. The centroids of the $Q_{-1}(.)$ and $Q_1(.)$ of the quantizers (Fig. 1a) belong to the unidimensional lattice [3]:

$$\Lambda_{-1} = 2\Delta\mathbb{Z}, \tag{1}$$

$$\Lambda_1 = 2\Delta\mathbb{Z} + \Delta. \tag{2}$$

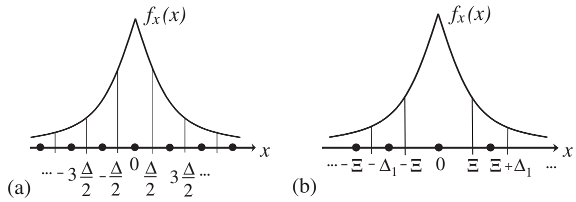

Fig. 1. Quantization of the Laplacian pdf: (a) uniform quantizer case, (b) the UDQ case.

Therefore, the stego image y' is obtained as a quantized version of the host data:

$$y' = Q_b(x) = x + w, \tag{3}$$

where $b \in \{-1; +1\}$ and the watermark w is equivalent to the quantization error:

$$w = Q_b(x) - x. \tag{4}$$

Supposing that high rate quantization conditions are preserved [4], the following assumptions are valid:

(a) the watermark and the host signal are independent;
(b) quantization error is uniformly distributed within the interval $[-\Delta; \Delta]$;
(c) embedding distortions are determined by $D_W = \Delta^2/3$ [3].

The DM decoder performs the minimum distance decoding:

$$\hat{b} = \arg \min_{b\in\{-1,+1\}} \|y - Q_b(y)\|^2, \tag{5}$$

where y is the input of the decoder.

2.2. Distortion compensated dither modulation

In case of the distortion compensated dither modulation (DC-DM) the watermark (4) is scaled by a certain constant $v \in [0; 1]$ (for $v = 1$ the DC-DM reduces to the DM) [6]:

$$w = ve = v(Q_b(x) - x), \tag{6}$$

$$y' = x + w = x + v(Q_b(x) - x). \tag{7}$$

Therefore, the error of quantization is uniformly distributed on the interval $[-v\Delta; v\Delta]$ and the embedding distortions are given by $D_W = v^2\Delta^2/3$ and decoding is also performed using minimum distance rule (5).

As it was pointed out in the Introduction, in the field of lossy image compression uniform quantizer rate-distortion performance improvement can be obtained for the case of Laplacian or GGd pdf using simple modification. In this case the width of the central bin (deadzone) of the midtread quantizer is enlarged from $[-\Delta/2; \Delta/2)$ to $[-\Xi; \Xi)$ [5].

Assuming i.i.d. Laplacian distribution of the host image that was successfully used in lossy wavelet based image compression [7], one might expect performance enhancement of DM and DC-DM providing better communications conditions for near-zero magnitude coefficients using wider deadzone in comparison with the regular bin width (Fig. 1b). The improvement is coming from enlargement of the minimum code distance for the most often appearing host elements.

Several investigations have been carried out in source coding to determine the optimal deadzone-to-regular bin width $(2\Xi/\Delta)$ ratio [8,9]. It was shown that it should be in the range between 1.5 and 2. In our case we select $2\Xi/\Delta = 2$ and take the same quantizer structure for both symbols (Fig. 2b). We will refer to

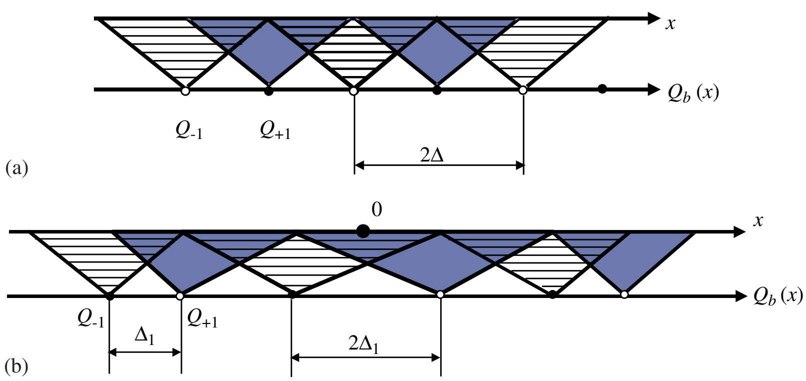

Fig. 2. DM watermark signaling: (a) classical system, (b) UDQ-based system.

the quantization-based watermarking systems that use the UDQ as to the *deadzone-based DM* (DDM) and *deadzone-based DC-DM* (DDC-DM), respectively.

3. Performance analysis of DDM and DDC-DM watermarking

Performance analysis of deadzone-based known-host-state methods will be accomplished for cases of uniform noise and AWGN attacks, assuming i.i.d. Laplacian distribution of the host image, and is based on the methodology developed in [3]. All the justifications are performed based on the assumption that high rate quantization conditions are preserved within the deadzones.

Assume that the stego image y' is corrupted by some additive noise z with a pdf $f_Z(z)$ independent with the host signal that is $y = y' + z = x + w + z$. In this case, referring to $\mathcal{G}_{-1}$ and $\mathcal{G}_{+1}$ as to the decision regions associated to $\hat{b} = -1$ and $\hat{b} = +1$, respectively, bit error rate probability is determined by the following expression:

$$P_\mathrm{e} = P\{\|y - Q_{+1}(y)\|^2 < \|y - Q_{-1}(y)\|^2 | b = -1\} \\ = P\{y \in \mathcal{G}_1 | b = -1\} \tag{8}$$

and can be calculated in the following way:

$$P_\mathrm{e} = \int_{\mathcal{G}_1} f_Y(y|b = -1) = \int_{\mathcal{G}_1} f_\Phi(\phi)\,\mathrm{d}\phi, \tag{9}$$

where $f_\Phi(\phi)$ is the equivalent noise pdf that depends on both embedding and attacking strategies and is determined by a convolution of “self noise” pdf with the pdf of the attack [3].

The difference between classical methods and DDM and DDC-DM consists in dependence of this probability on the bin $Q_{-1}(.)$ where x lies. Therefore, for proper analysis it is now necessary to determine the UDQ parameters and to compute this probability for all the bins where x can be located.

3.1. Determination of the UDQ parameters

According to the selection made in Section 2.2, the ratio of deadzone width to the regular bin width is equal to 2.

In order to determine the regular bin width of the UDQ one needs to solve the following equation:

$$\frac{\Delta_1^2}{6}(\mathrm{e}^{-2.5\lambda\Delta_1}+\mathrm{e}^{-\lambda\Delta_1})+\frac{4\Delta_1^2}{3}\times(1-\mathrm{e}^{-2.5\lambda\Delta_1}-\mathrm{e}^{-\lambda\Delta_1})-D_{\mathrm{W}}=0, \tag{10}$$

where Δ, Δ_1 are the bin width of the uniform quantizer and regular bin width of the UDQ, respectively; λ is the parameter of Laplacian distribution. This equation is obtained assuming the embedding distortions introduced by the UDQ to be $D_{\mathrm{W}}^{\mathrm{D}}=\Delta_1^2/3(1-P_{\mathrm{D}})+(4\Delta_1^2/3)P_{\mathrm{D}}$, where $P_{\mathrm{D}}=\int_{-\Delta_1}^{2.5\Delta_1}(\lambda/2)\exp(-\lambda|x|)\,\mathrm{d}x=1-\mathrm{e}^{-2.5\lambda\Delta_1}-\mathrm{e}^{-\lambda\Delta_1}$ is the probability that Laplacian distribution sample lie on the interval $[-\Delta_1;2.5\Delta_1)$.

Parameter λ can be determined for the given watermark-to-image ratio (WIR), $\mathrm{WIR}=10\log_{10}(\sigma_{\mathrm{W}}^2/\sigma_X^2), \sigma_{\mathrm{W}}^2=D_{\mathrm{W}}, \sigma_X^2=2/\lambda^2$, that for the case of this paper is assumed to be $\mathrm{WIR}_1=-6\,\mathrm{dB}$ and $\mathrm{WIR}_2=-16\,\mathrm{dB}$. Thus, for both DDM and DDC-DM one has

$$\lambda=\sqrt{\frac{2}{D_{\mathrm{W}}}10^{0.1\mathrm{WIR}}}. \tag{11}$$

3.2. DM: uniform noise attack

In case of the uniform noise attack one can assume that $\phi=z$ and z is uniformly distributed with the following pdf:

$$f_{\Phi}(\phi)=\begin{cases}\dfrac{1}{2\eta} & \text{if } \phi\in[Q_b(x)-\eta,Q_b(x)+\eta],\\ 0 & \text{otherwise,}\end{cases} \tag{12}$$

where η is within the interval $\eta\in[\Delta\sqrt{10^{-0.1\mathrm{WNR}_{\max}}},\Delta\sqrt{10^{-0.1\mathrm{WNR}_{\min}}}]$ and $\mathrm{WNR}=10\log_{10}(\sigma_{\mathrm{W}}^2/\sigma_Z^2)$ denotes the watermark-to-noise ratio.

Thus, assuming mean-square error (MSE) distortion measure, attacking distortions are equal to the noise variance, $D_Z=\eta^2/3$. Taking into account that different bins have different robustness to the noise, one can obtain based on (9):

$$P_{\mathrm{e}}^{d}=\begin{cases}0 & \text{if } \eta\leqslant\Delta_1,\\ (1-0.5\mathrm{e}^{-\lambda\Delta_1}-0.5\mathrm{e}^{-2.5\lambda\Delta_1})\left(1-\dfrac{\Delta_1}{\eta}\right) & \text{if } \Delta_1<\eta\leqslant 2\Delta_1,\\ (1-0.5\mathrm{e}^{-\lambda\Delta_1}-0.5\mathrm{e}^{-2.5\lambda\Delta_1})0.5 & \text{if } 2\Delta_1<\eta\leqslant\eta_{\max};\end{cases} \tag{13}$$

$$P_{\mathrm{e}}^{1}=\begin{cases}0 & \text{if } \eta\leqslant\dfrac{\Delta_1}{2},\\ (0.5\mathrm{e}^{-\lambda\Delta_1}-0.5\mathrm{e}^{-3.5\lambda\Delta_1})\left(1-\dfrac{\Delta_1}{2\eta}\right) & \text{if } \dfrac{\Delta_1}{2}<\eta\leqslant\dfrac{3\Delta_1}{2},\\ (0.5\mathrm{e}^{-\lambda\Delta_1}-0.5\mathrm{e}^{-3.5\lambda\Delta_1})\left(0.5+\dfrac{\Delta_1}{4\eta}\right) & \text{if } \dfrac{3\Delta_1}{2}<\eta\leqslant\dfrac{7\Delta_1}{2},\\ (0.5\mathrm{e}^{-\lambda\Delta_1}-0.5\mathrm{e}^{-3.5\lambda\Delta_1})\dfrac{2\Delta_1}{\eta} & \text{if } \dfrac{7\Delta_1}{2}<\eta\leqslant\eta_{\max};\end{cases} \tag{14}$$

$$P_e^2 = \begin{cases} 0 & \text{if } \eta \leqslant \frac{\Delta_1}{2}, \\ (0.5e^{-2.5\lambda\Delta_1} - 0.5e^{-4.5\lambda\Delta_1})\left(1 - \frac{\Delta_1}{2\eta}\right) & \text{if } \frac{\Delta_1}{2} < \eta \leqslant \frac{3\Delta_1}{2}, \\ (0.5e^{-2.5\lambda\Delta_1} - 0.5e^{-4.5\lambda\Delta_1})\frac{\Delta_1}{\eta} & \text{if } \frac{3\Delta_1}{2} < \eta \leqslant 3\Delta_1, \\ 0.5e^{-2.5\lambda\Delta_1} - 0.5e^{-4.5\lambda\Delta_1})\left(0.5 - \frac{\Delta_1}{4\eta}\right) & \text{if } 3\Delta_1 < \eta \leqslant \eta_{\max}; \end{cases} \tag{15}$$

$$P_e^3 = \begin{cases} 0 & \text{if } \eta \leqslant \frac{\Delta_1}{2}, \\ (0.5e^{-3.5\lambda\Delta_1} - 0.5e^{-5.5\lambda\Delta_1})\left(1 - \frac{\Delta_1}{2\eta}\right) & \text{if } \frac{\Delta_1}{2} < \eta \leqslant \frac{3\Delta_1}{2}, \\ (0.5e^{-3.5\lambda\Delta_1} - 0.5e^{-5.5\lambda\Delta_1})\frac{\Delta_1}{\eta} & \text{if } \frac{3\Delta_1}{2} < \eta \leqslant \frac{5\Delta_1}{2}, \\ (0.5e^{-3.5\lambda\Delta_1} - 0.5e^{-5.5\lambda\Delta_1})\left(1 - \frac{3\Delta_1}{2\eta}\right) & \text{if } \frac{5\Delta_1}{2} < \eta \leqslant \frac{7\Delta_1}{2}, \\ 0.5e^{-3.5\lambda\Delta_1} - 0.5e^{-5.5\lambda\Delta_1})\left(0.5 + \frac{\Delta_1}{4\eta}\right) & \text{if } \frac{7\Delta_1}{2} < \eta \leqslant \eta_{max}; \end{cases} \tag{16}$$

$$P_e^4 = \begin{cases} 0 & \text{if } \eta \leqslant \frac{\Delta_1}{2}, \\ (0.5e^{-4.5\lambda\Delta_1} + 0.5e^{-5.5\lambda\Delta_1})\left(1 - \frac{\Delta_1}{2\eta}\right) & \text{if } \frac{\Delta_1}{2} < \eta \leqslant \frac{3\Delta_1}{2}, \\ (0.5e^{-4.5\lambda\Delta_1} + 0.5e^{-5.5\lambda\Delta_1})\frac{\Delta_1}{\eta} & \text{if } \frac{3\Delta_1}{2} < \eta \leqslant \frac{5\Delta_1}{2}, \\ (0.5e^{-4.5\lambda\Delta_1} + 0.5e^{-5.5\lambda\Delta_1})\left(1 - \frac{3\Delta_1}{2\eta}\right) & \text{if } \frac{5\Delta_1}{2} < \eta \leqslant \frac{7\Delta_1}{2}, \\ 0.5e^{-4.5\lambda\Delta_1} + 0.5e^{-5.5\lambda\Delta_1})\frac{2\Delta_1}{\eta} & \text{if } \frac{7\Delta_1}{2} < \eta \leqslant \eta_{\max}, \end{cases} \tag{17}$$

where P_e^d, P_e^1, P_e^2, P_e^3 and P_e^4 are bit error rate probabilities for the cases when x is located within the intervals $[-\Delta_1, 2.5\Delta_1)$, $[-3.5\Delta_1, -\Delta_1)$, $[2.5\Delta_1, 4.5\Delta_1)$, $[-5.5\Delta_1, -3.5\Delta_1)$ and $(-\infty, -5.5\Delta_1) \cup [4.5\Delta_1, +\infty)$, respectively, $\eta_{\max} = \Delta\sqrt{10^{-0.1\mathrm{WNR}_{\min}}}$, is the maximal value of the attacking noise, $\mathrm{WNR}_{\min}$ is the minimal WNR for the targeting range.

Finally, bit error rate probability is given by the sum of its components:

$$P_e^{\mathrm{DDM}} = P_e^d + P_e^1 + P_e^2 + P_e^3 + P_e^4. \tag{18}$$

Like in case of the classical DM, one can claim about "provable robustness" of the DDM [3] due to zero bit error rate probability, if the noise is concentrated within the interval $[-\Delta_1/2, \Delta_1/2]$.

3.3. DC-DM: uniform noise attack

For the analysis of the DDC-DM we assume the following conditions [3]: $v = 0.53$ and $\eta \geqslant (1-v)\Delta_1$. Taking into account different bin width and due to the "self-noise" one can find

$$f_\Phi^d(\phi) = \begin{cases} \dfrac{1}{2\eta} & \text{if } |\phi| \leqslant \eta - (1-v)2\Delta_1, \\ \dfrac{\eta + (1-v)2\Delta_1 - |\phi|}{8\Delta_1\eta(1-v)} & \text{if } \eta - (1-v)2\Delta_1 < |\phi| \leqslant \eta - (1-v)2\Delta_1; \end{cases} \tag{19}$$

$$f_\Phi^{\overline{d}}(\phi) = \begin{cases} \dfrac{1}{2\eta} & \text{if } |\phi| \leqslant \eta - (1-v)\Delta_1, \\ \dfrac{\eta + (1-v)\Delta_1 - |\phi|}{4\Delta_1\eta(1-v)} & \text{if } \eta - (1-v)\Delta_1 < |\phi| \leqslant \eta - (1-v)\Delta_1, \end{cases} \tag{20}$$

where $f_\Phi^d(\phi)$ and $f_\Phi^{\overline{\phi}}(\phi)$ are equivalent noise pdfs in the deadzones and the rest of the bins, respectively.

Using similar approach as in case of the DDM, one obtains

$$P_e^d = \begin{cases} 0 & \text{if } \eta \leqslant 2\Delta_1(v-0.5), \\ (1 - 0.5e^{-\lambda\Delta_1} - 0.5e^{-2.5\lambda\Delta_1}) \\ \quad \times \dfrac{(\eta - 2\Delta_1(v-0.5))^2}{8\Delta_1\eta(1-v)} & \text{if } 2\Delta_1(v-0.5) \leqslant \eta \leqslant 2\Delta_1 v, \\ (1 - 0.5e^{-\lambda\Delta_1} - 0.5e^{-2.5\lambda\Delta_1}) \\ \quad \times \left(\dfrac{(\eta - 2\Delta_1(v-0.5))^2}{8\Delta_1\eta(1-v)} - \dfrac{(\eta - 2\Delta_1(v-0.5))^2}{16\Delta_1\eta(1-v)}\right) & \text{if } 2\Delta_1(v-0.5) < \eta \leqslant \eta_{\max}, \end{cases} \tag{21}$$

$$P_e^1 = \begin{cases} 0 & \text{if } \eta \leqslant \Delta_1(v-0.5), \\ 0.5(e^{-\lambda\Delta_1} - e^{-3.5\lambda\Delta_1}) \\ \quad \times \dfrac{(\eta - \Delta_1(v-0.5))^2}{4\Delta_1\eta(1-v)} & \text{if } \Delta_1(v-0.5) < \eta \leqslant \Delta_1(1.5-v), \\ 0.5(e^{-\lambda\Delta_1} - e^{-3.5\lambda\Delta_1}) \\ \quad \times \left(1 - \dfrac{\Delta_1}{2\eta}\right) & \text{if } \Delta_1(1.5-v) < \eta \leqslant \Delta_1(0.5+v), \\ 0.5(e^{-\lambda\Delta_1} - e^{-3.5\lambda\Delta_1}) \\ \quad \times (1 - \dfrac{\Delta_1}{2\eta} - \dfrac{(\eta - (0.5+v)\Delta_1)^2}{8\Delta_1\eta(1-v)}) & \text{if } \Delta_1(0.5+v) < \eta \leqslant \Delta_1(2.5-v), \\ 0.5(e^{-\lambda\Delta_1} - e^{-3.5\lambda\Delta_1}) \\ \quad \times (0.5 + \frac{\Delta_1}{4\eta}) & \text{if } \Delta_1(0.5+v) < \eta \leqslant \eta_{\max}, \end{cases} \tag{22}$$

$$P_{\rm e}^2 = \begin{cases} 0 & \text{if } \eta \leqslant \Delta_1(v-0.5), \\ 0.5({\rm e}^{-2.5\lambda\Delta_1} + {\rm e}^{-3.5\lambda\Delta_1}) \\ \quad \times \dfrac{(\eta - \Delta_1(v-0.5))^2}{4\Delta_1\eta(1-v)} & \text{if } \Delta_1(v-0.5) < \eta \leqslant \Delta_1(1.5-v), \\ 0.5({\rm e}^{-2.5\lambda\Delta_1} + {\rm e}^{-3.5\lambda\Delta_1}) \\ \quad \times (1 - \dfrac{\Delta_1}{2\eta}) & \text{if } \Delta_1(1.5-v) < \eta \leqslant \Delta_1(0.5+v), \\ 0.5({\rm e}^{-2.5\lambda\Delta_1} + {\rm e}^{-3.5\lambda\Delta_1}) \\ \quad \times \left(1 - \dfrac{\Delta_1}{2\eta} - \dfrac{(\eta - (0.5+v)\Delta_1)^2}{4\Delta_1(1-v)\eta}\right) & \text{if } \Delta_1(0.5+v) < \eta \leqslant \Delta_1(2.5-v), \\ 0.5({\rm e}^{-2.5\lambda\Delta_1} + {\rm e}^{-3.5\lambda\Delta_1})\dfrac{\Delta_1}{\eta} & \text{if } \Delta_1(2.5-v) < \eta \leqslant \eta_{\max}. \end{cases} \tag{23}$$

As in case of the DDM, bit error rate probability is determined by summation of (21)–(23):

$$P_{\rm e}^{\text{DDC-DM}} = P_{\rm e}^d + P_{\rm e}^1 + P_{\rm e}^2. \tag{24}$$

Again one can observe "provable robustness" of the DDC-DM for the case when $\eta \leqslant \Delta_1(v-0.5)$.

3.4. DM: AWGN attack

Having determined parameters of the UDQ and assuming that the stego image is attacked by the AWGN with zero mean and variance equal to σ_Z^2, one can find:

$$\begin{aligned} P_{\rm e}^{\rm DDM} &= (1 - 0.5{\rm e}^{-\lambda\Delta_1} - 0.5{\rm e}^{-2.5\lambda\Delta_1}) \\ &\quad \times \left\{ 2Q\left(\frac{\Delta_1}{\sigma_N}\right) - Q\left(\frac{2\Delta_1}{\sigma_N}\right) \right\} \\ &\quad + (0.5{\rm e}^{-\lambda\Delta_1} + 0.5{\rm e}^{-2.5\lambda\Delta_1}) \\ &\quad \times \sum_{i=1}^{\infty} Q\left(\frac{(4i-3)\Delta_1}{2\sigma_N}\right) + Q\left(\frac{(4i-1)\Delta_1}{2\sigma_N}\right) \\ &\quad - (2P_{2i-1} + P_{2i})Q\left(\frac{(4i+1)\Delta_1}{2\sigma_N}\right) \\ &\quad + (P_{2i-1} + 2P_{2i})Q\left(\frac{(4i+3)\Delta_1}{2\sigma_N}\right) \\ &\quad - P_{2i}Q\left(\frac{(4i+5)\Delta_1}{2\sigma_N}\right), \end{aligned} \tag{25}$$

where P_i is a probability of ith bin, $Q(x)$ is a Q-function, $Q(x) = 1/\sqrt{2\pi}\int_x^{\infty} {\rm e}^{-(t^2/2)}$.

3.5. DC-DM: AWGN attack

In case of the DDC-DM, the equivalent noise pdf is obtained as was the convolution of the uniformly distributed self noise with Gaussian attack noise. Thus, this probability density is given by

$$f_{\Phi}^{d}(\phi) = \frac{1}{4\Delta_1(1-v)}\left\{Q\left(\frac{\phi - 2\Delta_1(1-v)}{\sigma_N}\right) - Q\left(\frac{\phi + 2\Delta_1(1-v)}{\sigma_N}\right)\right\}; \tag{26}$$

$$f_{\Phi}^{\bar{d}}(\phi) = \frac{1}{2\Delta_1(1-v)}\left\{Q\left(\frac{\phi - \Delta_1(1-v)}{\sigma_N}\right) - Q\left(\frac{\phi + \Delta_1(1-v)}{\sigma_N}\right)\right\}, \tag{27}$$

where $f_{\Phi}^{d}(\phi)$ and $f_{\Phi}^{\bar{d}}(\phi)$ have the same meanings as in case of (19) and (20).

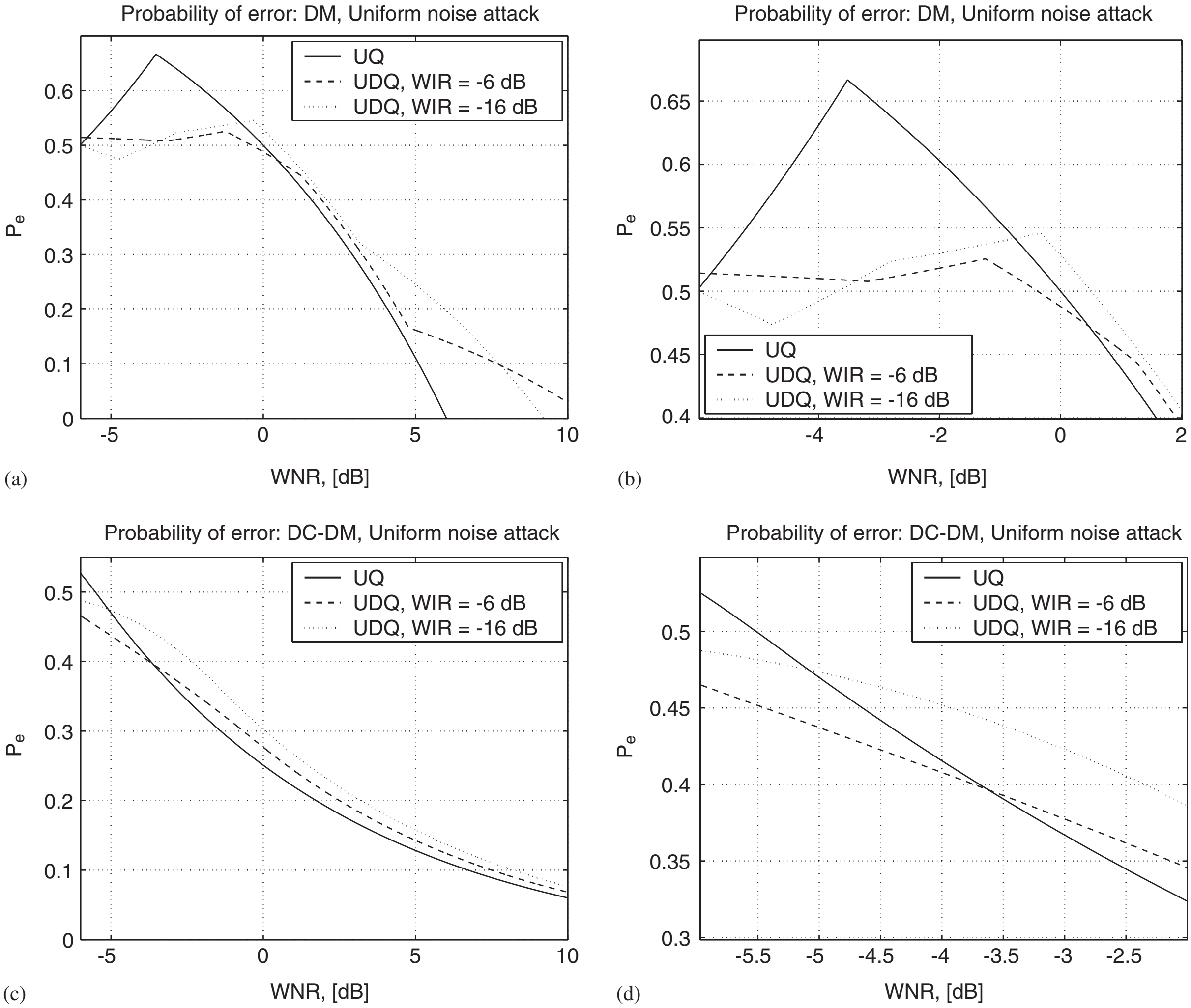

Fig. 3. Bit error rate probabilities (a) and (b) of the DDM versus the DM and (c) and (d) the DDC-DM versus the DC-DM in case of the uniform noise attack for WIR $= -6\,\text{dB}$ and WIR $= -16\,\text{dB}$.

Therefore, it is possible to demonstrate that bit error rate probability of the DDC-DM undergo AWGN attack is determined by

$$\begin{aligned} P_{\mathrm{e}}^{\text{DDC-DM}} = {} & (1 - 0.5\mathrm{e}^{-\lambda\Delta_1} - 0.5\mathrm{e}^{-2.5\lambda\Delta_1}) \\ & \times\left(\int_{\Delta_1}^{2\Delta_1} f_{\Phi}^{d}(\phi)\,\mathrm{d}\phi + \int_{\Delta_1}^{\infty} f_{\Phi}^{d}(\phi)\,\mathrm{d}\phi\right) \\ & + (0.5\mathrm{e}^{-\lambda\Delta_1} + 0.5\mathrm{e}^{-2.5\lambda\Delta_1}) \\ & \times \sum_{i=1}^{\infty} \int_{(4i-3)\Delta_1/2}^{(4i-1)\Delta_1/2} f_{\Phi}^{\bar{d}}(\phi)\,\mathrm{d}\phi \\ & + \sum_{i=1}^{\infty} P_{2i-1} \int_{(4i-1)\Delta_1/2}^{(4i+1)\Delta_1/2} f_{\Phi}^{\bar{d}}(\phi)\,\mathrm{d}t \\ & + (P_{2i-1} + P_{2i}) \int_{(4i+1)\Delta_1/2}^{(4i+3)\Delta_1/2} f_{\Phi}^{\bar{d}}(\phi)\,\mathrm{d}\phi \\ & + P_{2i} \int_{(4i+3)\Delta_1/2}^{(4i+5)\Delta_1/2} f_{\Phi}^{\bar{d}}(\phi)\,\mathrm{d}\phi. \end{aligned} \tag{28}$$

4. Experimental results

In this Section we present the results of benchmarking of DDM and DDC-DM watermarking methods versus classical DM and DC-DM in terms of the bit error rate probability under AWGN and uniform noise attacks. As it was already mentioned in the previous Sections, the analysis is performed for two different WIRs, i.e. $\mathrm{WIR}_1 = -6\,\mathrm{dB}$ and $\mathrm{WIR}_2 = -16\,\mathrm{dB}$. Two target ranges of WNR are of interest: $\mathrm{WNR} \in [-6; 10]\,\mathrm{dB}$ for the case of the uniform noise attack and $\mathrm{WNR} \in [-15; 10]\,\mathrm{dB}$ for the additive Gaussian attack case. The compensation parameter of the DDC-DM is chosen to be equal to $v = 0.53$ for the case of uniform noise attack and $v = 0.5$ for the case of AWGN attack to be coherent with the analysis performed in [3].

The results of benchmarking are presented in Figs. 3 and 4 as well as in Table 1. These results allow to claim that development of the known-host-state watermarking methods taking into account the statistics of the host data leads to their performance improvement in terms of bit error rate probability of both DM and DC-DM for the case of negative WNRs.

However, the performance of the proposed UDQ-based data-hiding methods sacrifices at higher WNRs from the reduction of the regular bin width of UDQ contrarily to that one uses in the uniform quantizer under the condition that introduced quantization distortion are the same for both of them.

On the other hand, the obtained performance improvement is not as significant (especially for the DC-DM case) as it was expected. As one of the possible reasons for this we see that high rate quantization assumption is not realistic for the analyzed data-hiding set-up (in terms of "self noise" statistics). As the justification of this argument we presented in Fig. 5 the pdfs of the Laplacian data using the UDQ with the parameters exploited in the experimental part of the paper versus those obtained by dropping high-rate quantization assumption as well as the probability densities of the stego data attacked by both uniform noise and AWGN.

The presented results demonstrate that self noise pdf in the real case significantly deviates from being the train of rectangular pulses that consequently impacts the accuracy of the developed models for probability of error especially in the case of DDC-DM. Therefore, we see the adjustment of the developed models for

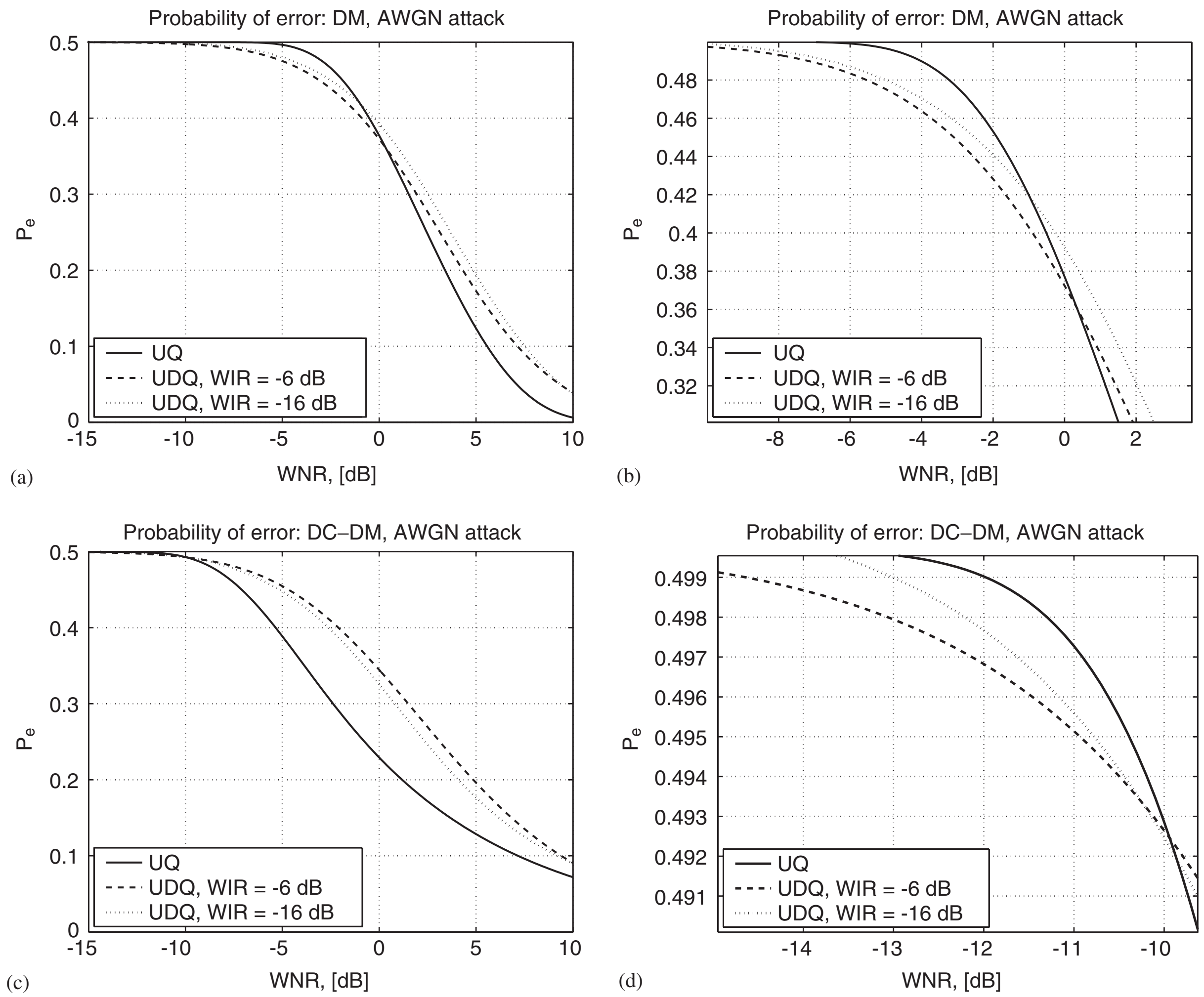

Fig. 4. Bit error rate probabilities (a) and (b) of the DDM versus the DM and (c) and (d) of the DDC-DM versus the DC-DM in case of the AWGN attack for WIR $= -6$ dB and WIR $= -16$ dB.

Table 1
Bit error rate probability performance of classical and UDQ-based data-hiding methods undergo uniform noise and AWGN attacks

Embedding method	Uniform noise		AWGN	
	WIR $= -6$ dB	WIR $= -16$ dB	WIR $= -6$ dB	WIR $= -16$ dB
DM, WNR $= -3$ dB	0.64	0.64	0.48	0.48
DDM, WNR $= -3$ dB	0.51	0.52	0.45	0.46
DC-DM, WNR $= -6$ dB	0.53	0.53	0.5	0.5
DDC-DM, WNR $= -13$ dB	0.47	0.49	0.498	0.499

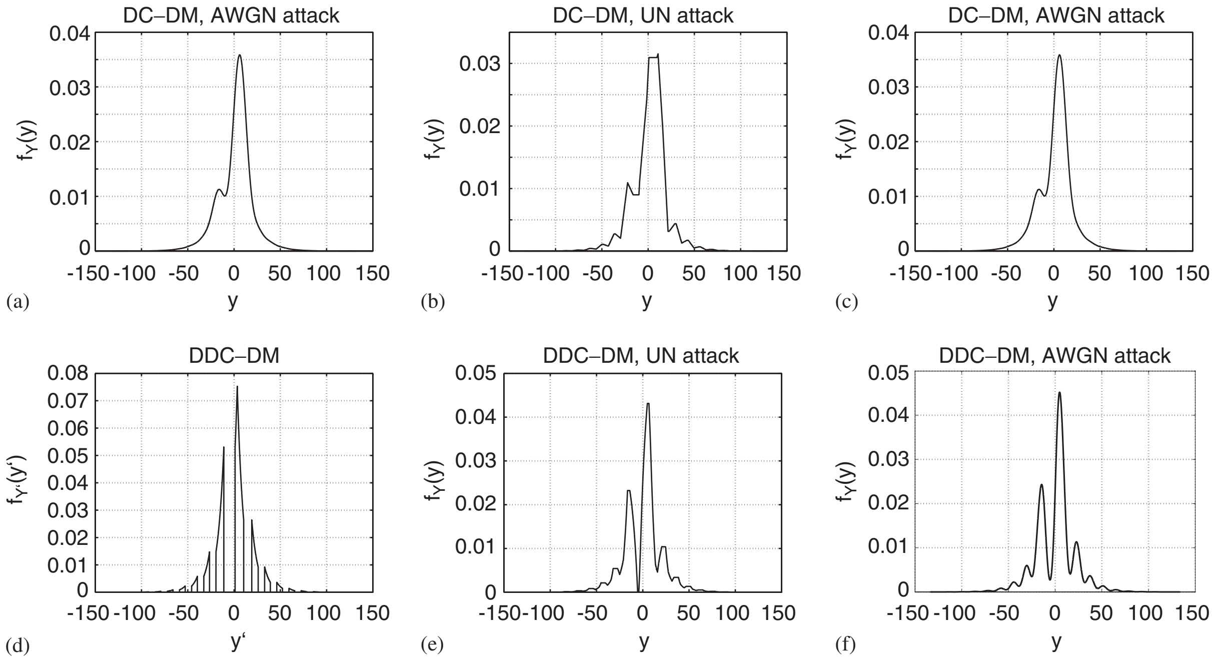

Fig. 5. Probability density functions of DDC-DM output for the case when message $b = -1$ is communicated obtained from the Laplacian host under the high-rate quantization assumption versus real DDC-DM output pdfs: (a) and (d) pdfs of the stego data ($v = 0.53$); (b) and (e) pdfs of the stego data attacked by the UN ($v = 0.53$); (c) and (f) pdfs of the stego data attacked by the AWGN ($v = 0.5$). $2\Xi/\Delta_1 = 2$, $v = 0.53$, $D_{\text{emb}} = 10$, WIR $= -16$ dB and WNR $= 0$ dB.

probability of error computation to the statistical properties of real data as one of the possible ways of the performed analysis accuracy improvement.

Another direction we envisioned for the enhancement of performance of the UDQ-based data-hiding method consists in the optimization of the deadzone-to-regular bin width ratio for the fixed operational WNR that for the case of this research was considered to be fixed for the broad range of attacking noise variances.

5. Conclusions

In this paper we have considered the problem of quantization-based data-hiding performance improvement using proper stochastic modeling of the host image. In particular, we have been targeting improvement of performance of DM and DC-DM methods suffering from uniform noise and AWGN attacks in terms of bit error rate probability. We have adjusted existing design rules of DM and DC-DM by replacing usually applied uniform quantizer by UDQ elaborated for the global i.i.d. Laplacian model of the host data. We have obtained in the close form analytical expressions for bit error rate probability calculation of deadzone-based DM and deadzone-based DC-DM for the case of above-mentioned attacks. The obtained experimental results demonstrate performance improvement of DDM and DDC-DM versus classical DM and DC-DM at negative WNRs.

It should be pointed out that at positive WNRs performance loss of the modified techniques is observed. The reason for this is twofold: because of smaller regular bin width of the UDQ contrary to the uniform quantizer, when embedding distortion equivalence is used as one of design criteria, and due to the non-adequate assumption about the statistics of the stego data. In order to overcome this problem we propose to optimize the deadzone-to-regular bin width ratio for particular WNR as well as to adopt the developed models to the real data statistics.

Other our future research lines consist in the extension of the presented analysis to the class of GG host data as well as its extension to the multidimensional case. Finally, a practical UDQ-based data-hiding method will be developed to validate the obtained theoretical results.

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