SINR, BIT ERROR RATE, AND SHANNON CAPACITY OPTIMIZED SPREAD-SPECTRUM STEGANOGRAPHY*

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ABSTRACT

For any given host image and (block) transform domain of interest, we derive the signature vector that when used for spread-spectrum (SS) message embedding maximizes the signal-to-interference-plus-noise ratio (SINR) at the output of the maximum SINR linear filter receiver. Under a (colored) Gaussian assumption on the transform domain host data, we see that the same signature offers minimum probability of error message recovery at any host distortion level or -conversely- minimizes the host distortion for any probability of error target level. In addition, we show that the same signature maximizes the Shannon capacity of the covert link. All developments are then generalized to cover SS embedding in linearly processed block transform domain host data with orders of magnitude demonstrated improvement over current SS steganographic practices.

1. INTRODUCTION

Spread-spectrum (SS) embedding algorithms for blind image steganography (that is, message recovery without knowledge of the original image) have been based on the understanding that the host image acts as a source of interference to the secret message of interest [1]-[5]. Yet, it should also be understood that this interference is known to the message embedder [6] and optimized embedding methods can facilitate host interference suppression at the receiver side.

In this paper, for any given image, (block) transform domain, and host bins, we design an additive SS embedding scheme that maximizes the output signal-to-interference-plus-noise ratio (SINR) of the linear maximum SINR receiver filter. We establish that, under a (colored) Gaussian assumption on the host bins, this same scheme minimizes the receiver bit error rate (BER) at any mean square (MS) image distortion level, and maximizes the Shannon capacity of the covert link. We then generalize our findings to cover joint signature and linear host data projection optimization along the same lines. In this present work, we consider only scalar parameterized host data projection as in [5].

2. SIGNAL MODEL AND NOTATION

Consider a host image $\mathbf{H} \in \mathcal{M}^{N_1 \times N_2}$ that is to be watermarked where $\mathcal{M}$ is the image alphabet and $N_1 \times N_2$ is the image size in pixels. Without loss of generality, the image $\mathbf{H}$ is broken into P local blocks of size $\frac{N_1 \times N_2}{P}$ pixels. Each block $\mathbf{H}_1, \mathbf{H}_2, \cdots, \mathbf{H}_P$ is to carry one hidden information bit $b_p \in \{\pm 1\}$, $p = 1, 2, \cdots, P$, respectively. Embedding is performed in a real 2-dimensional transform domain $\mathcal{T}$. After transform calculation and conventional zig-zag scanning vectorization, we obtain $\mathcal{T}(\mathbf{H}_p) \in \mathbb{R}^{\frac{N_1 \times N_2}{P}}$, $p = 1, 2, \cdots, P$. From the transform domain vectors $\mathcal{T}(\mathbf{H}_p)$ we choose a fixed subset of $L \leq \frac{N_1 \times N_2}{P}$ coefficients (bins) to form the final host vectors $\mathbf{x}_p \in \mathbb{R}^L$, $p = 1, 2, \cdots, P$ (for example, it is common and appropriate to exclude the dc coefficient).

The autocorrelation matrix of the host data $\mathbf{x}$,

$$\mathbf{R}_x \triangleq \frac{1}{P} \sum_{p=1}^{P} \mathbf{x}_p \mathbf{x}_p^T, \tag{1}$$

is an important statistical quantity for our developments. It is easy to see that in general $\mathbf{R}_x \neq c\mathbf{I}_L$, $c > 0$, where $\mathbf{I}_L$ is the size-L identity matrix; that is, $\mathbf{R}_x$ is not constant-value diagonal or "white" in field language.

3. SIGNATURE OPTIMIZATION

Consider direct additive SS embedding of the form

$$\mathbf{y} = Ab\mathbf{s} + \mathbf{x} + \mathbf{n} \tag{2}$$

where $A > 0$ is the bit amplitude, $\mathbf{s} \in \mathbb{R}^L$, $\|\mathbf{s}\| = 1$, is the (normalized) embedding signature to be designed, and $\mathbf{n} \sim$

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$\mathcal{N}\left(\mathbf{0}, \sigma_n^2 \mathbf{I}_L\right)$ represents potential external white Gaussian noise[1] of variance σ_n^2. The mean squared distortion of the original image *due to the watermark only* is

$$\mathcal{D} = E\left\{\|Ab\mathbf{s} + \mathbf{x} - \mathbf{x}\|^2\right\} = A^2. \quad (3)$$

With signal of interest $Ab\mathbf{s}$ and total disturbance $\mathbf{x}+\mathbf{n}$ in (2), the linear filter that operates on $\mathbf{y}$ and offers maximum SINR at its output is $\mathbf{w}_{\text{maxSINR}} = \left(\mathbf{R}_x + \sigma_n^2 \mathbf{I}_L\right)^{-1}\mathbf{s}$. The exact maximum output SINR value attained is $\text{SINR}_{\text{max}} = A^2 \mathbf{s}^T \left(\mathbf{R}_x + \sigma_n^2 \mathbf{I}_L\right)^{-1}\mathbf{s}$. We propose to view SINR_{max} as a function of the embedding signature $\mathbf{s}$, $\text{SINR}_{\text{max}}(\mathbf{s})$, and identify the signature that maximizes the SINR at the output of the maximum SINR filter. Our findings are presented in the form of a proposition below.

Proposition 1 *Consider additive SS embedding according to (2). Let $\mathbf{q}_1, \mathbf{q}_2, \cdots, \mathbf{q}_L$ be eigenvectors of $\mathbf{R}_x$ in (1) with corresponding eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_L$. For any watermark induced distortion level $\mathcal{D}$, a signature that maximizes the output SINR of the maximum SINR filter is*

$$\mathbf{s}^{opt} = \arg\max_{\mathbf{s}} \left\{A^2 \mathbf{s}^T \left(\mathbf{R}_x + \sigma_n^2 \mathbf{I}_L\right)^{-1}\mathbf{s}\right\} = \mathbf{q}_L. \quad (4)$$

When $\mathbf{s} = \mathbf{q}_L$, the output SINR is maximized to

$$SINR_{max}(\mathbf{q}_L) = \frac{A^2}{\lambda_L + \sigma_n^2} = \frac{\mathcal{D}}{\lambda_L + \sigma_n^2} \quad (5)$$

and maximum SINR data filtering simplifies to $\mathbf{w}_{maxSINR}^T\mathbf{y} = \mathbf{q}_L^T(\mathbf{R}_x + \sigma_n^2\mathbf{I}_L)^{-1}\mathbf{y} \equiv \mathbf{q}_L^T\mathbf{y}$. □

In summary, Proposition 1 says that the "minimum" eigenvector of the host data autocorrelation matrix, when used as the embedding signature, sends the output SINR to its maximum possible value $\frac{\mathcal{D}}{\lambda_L+\sigma_n^2}$. At the same time, maximum SINR filtering becomes plain signature (eigenvector) matched filtering.

If, in addition, we are allowed to assume that $\mathbf{x}$ is Gaussian, $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_x)$, then $\hat{b} = \text{sign}(\mathbf{w}_{\text{maxSINR}}^T\mathbf{y})$ is the optimum (minimum probability of error) bit detector with probability of error $P_e = Q\left(A\sqrt{\mathbf{s}^T(\mathbf{R}_x + \sigma_n^2\mathbf{I}_L)^{-1}\mathbf{s}}\right) = Q\left(\sqrt{\text{SINR}_{\text{max}}(\mathbf{s})}\right)$ where $Q(a) = \int_a^\infty \frac{1}{\sqrt{2\pi}} \exp^{\frac{-\tau^2}{2}} d\tau$. We see that P_e is a monotonically decreasing function of $\text{SINR}_{\text{max}}(\mathbf{s})$. We can view, then, P_e as a function of the embedding signature $\mathbf{s}$ and state the following proposition.

Proposition 2 *Consider additive SS embedding according to (2) with $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_x)$. Let $\mathbf{q}_1, \mathbf{q}_2, \cdots, \mathbf{q}_L$ be eigenvectors of $\mathbf{R}_x$ with corresponding eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_L$. For any watermark induced distortion level $\mathcal{D}$, a signature that minimizes the probability of error of the optimum bit detector is*

$$\mathbf{s}^{opt} = \arg\min_{\mathbf{s}} \left\{Q\left(A\sqrt{\mathbf{s}^T(\mathbf{R}_x + \sigma_n^2\mathbf{I}_L)^{-1}\mathbf{s}}\right)\right\} = \mathbf{q}_L. \quad (6)$$

When $\mathbf{s} = \mathbf{q}_L$, the probability of error of the optimum detector is minimized to

$$P_e(\mathbf{q}_L) = Q\left(\sqrt{\frac{\mathcal{D}}{\lambda_L + \sigma_n^2}}\right) \quad (7)$$

and optimum detection reduces to $\hat{b} = sign\left(\mathbf{q}_L^T\mathbf{y}\right)$. Conversely, for any pre-set probability of error level P_e, $\mathbf{s} = \mathbf{q}_L$ minimizes the watermark induced distortion to

$$\mathcal{D} = \left(\lambda_L + \sigma_n^2\right)\left[Q^{-1}\left(P_e\right)\right]^2. \quad (8)$$

□

Proposition 2 explains that under a Gaussian host data assumption the "minimum" eigenvector of the host data autocorrelation matrix, when used as the embedding signature, allows message recovery with the minimum possible bit error rate $Q\left(\sqrt{\frac{\mathcal{D}}{\lambda_L+\sigma_n^2}}\right)$ and trivial signature (eigenvector) matched filter detection. Conversely, the watermark induced image distortion $\mathcal{D}$ is minimized for any given target bit error rate.

If necessary, further bit error rate improvements below $Q\left(\sqrt{\frac{\mathcal{D}}{\lambda_L+\sigma_n^2}}\right)$ for any fixed distortion $\mathcal{D}$ can be attained via error correcting coding of the information bits at the expense of reduced information bit payload per image $\mathbf{H}$. The maximum possible payload in bits per image $\mathbf{H}$ that still allows -theoretically for asymptotically large number of image blocks P- message recovery with arbitrarily small probability of error is CP where $C = \max_{f_b} I(b;\mathbf{y})$ is the Shannon capacity of the covert link in bits per embedding attempt. We recall that $I(b;\mathbf{y})$ identifies the information conveyed about the embedded bit b by the received vector $\mathbf{y}$ and f_b denotes the bit probability distribution function. For Gaussian host data $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_x)$ and an average image distortion constraint $\mathcal{D}$, we can calculate

$$C = \frac{1}{2}\log\det\left(\mathbf{I}_L + \mathcal{D}\left(\mathbf{R}_x + \sigma_n^2\mathbf{I}_L\right)^{-1}\mathbf{s}\mathbf{s}^T\right) \quad (9)$$

where $\det(\cdot)$ is the determinant operator. We can show that the signature choice $\mathbf{s} = \mathbf{q}_L$ also maximizes the capacity C of the covert link and therefore the maximum allowable payload CP per cover image $\mathbf{H}$. The result is presented in the form of Proposition 3 below.

Proposition 3 *Consider additive SS embedding according to (2) with $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_x)$. Let $\mathbf{q}_1, \mathbf{q}_2, \cdots, \mathbf{q}_L$ be eigenvectors of $\mathbf{R}_x$ with corresponding eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_L$. For any watermark induced distortion level $\mathcal{D}$, a signature that maximizes the covert channel capacity is*

$$\mathbf{s}^{opt} = \arg\max_{\mathbf{s}} \left\{\frac{1}{2}\text{logdet}\left(\mathbf{I}_L + \mathcal{D}\left(\mathbf{R}_x + \sigma_n^2\mathbf{I}_L\right)^{-1}\mathbf{s}\mathbf{s}^T\right)\right\} = \mathbf{q}_L. \quad (10)$$

[1] Additive white Gaussian noise is frequently viewed as a suitable model for quantization errors, channel transmission disturbances, and/or image processing attacks.

When $\mathbf{s} = \mathbf{q}_L$*, the covert channel capacity is maximized to*

$$C(\mathbf{q}_L) = \frac{1}{2}\left(1 + \frac{\mathcal{D}}{\lambda_L + \sigma_n^2}\right) \tag{11}$$

information bits per embedding attempt. □

4. OPTIMIZED EMBEDDING IN LINEARLY TRANSFORMED HOST DATA

In this section, we assume that the host data vector $\mathbf{x}$ is linearly transformed [5] by an $L \times L$ real-valued operator of the form $\mathbf{I}_L - c\mathbf{s}\mathbf{s}^T$ where $c \in \mathbb{R}$ and $\mathbf{s}$ is the embedding signature. In parallel to (2), the composite signal now becomes

$$\mathbf{y} = Ab\mathbf{s} + (\mathbf{I}_L - c\mathbf{s}\mathbf{s}^T)\mathbf{x} + \mathbf{n} \tag{12}$$

and the mean squared distortion *due to the watermark only* is

$$\mathcal{D} = E\left\{\left\|\left(Ab - c\mathbf{s}^T\mathbf{x}\right)\mathbf{s}\right\|^2\right\} = A^2 + c^2\mathbf{s}^T\mathbf{R}_x\mathbf{s}. \tag{13}$$

With signal of interest $Ab\mathbf{s}$ and total disturbance $(\mathbf{I}_L - c\mathbf{s}\mathbf{s}^T)\mathbf{x} + \mathbf{n}$ in (12), the linear filter that operates on $\mathbf{y}$ and offers maximum SINR at its output is

$$\mathbf{w}_{\text{maxSINR}} = \left(\left(\mathbf{I}_L - c\mathbf{s}\mathbf{s}^T\right)\mathbf{R}_x\left(\mathbf{I}_L - c\mathbf{s}\mathbf{s}^T\right) + \sigma_n^2\mathbf{I}_L\right)^{-1}\mathbf{s}. \tag{14}$$

The exact maximum output SINR value attained is

$$\text{SINR}_{\text{max}} = A^2\mathbf{s}^T\left(\left(\mathbf{I}_L - c\mathbf{s}\mathbf{s}^T\right)\mathbf{R}_x\left(\mathbf{I}_L - c\mathbf{s}\mathbf{s}^T\right) + \sigma_n^2\mathbf{I}_L\right)^{-1}\mathbf{s}. \tag{15}$$

We look at SINR_{max} as a function of both the embedding signature $\mathbf{s}$ and the parameter c, $\text{SINR}_{\text{max}}(\mathbf{s}, c)$. In Proposition 4 below, we identify the $(\mathbf{s}, c)$ pair that jointly maximizes the SINR at the output of the maximum SINR filter.

Proposition 4 *Consider additive SS embedding in transformed host data according to (12). Let* $\mathbf{q}_1, \mathbf{q}_2, \cdots, \mathbf{q}_L$ *be eigenvectors of* $\mathbf{R}_x$ *with corresponding eigenvalues* $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_L$*. For any watermark induced distortion level* $\mathcal{D}$*, a (signature* $\mathbf{s}$*, parameter* c*) pair that maximizes the output SINR of the maximum SINR filter is*

$$\mathbf{s}^{opt} = \arg\max_{\mathbf{s}}\left\{A^2\mathbf{s}^T\left(\left(\mathbf{I}_L - c\mathbf{s}\mathbf{s}^T\right)\mathbf{R}_x\left(\mathbf{I}_L - c\mathbf{s}\mathbf{s}^T\right) + \sigma_n^2\mathbf{I}_L\right)^{-1}\mathbf{s}\right\} = \mathbf{q}_L \tag{16}$$

and $c^{opt} = \arg\max_{c}\left\{SINR_{max}(\mathbf{s}^{opt}, c)\right\}$

$$= \frac{\lambda_L + \sigma_n^2 + \mathcal{D} - \sqrt{(\lambda_L + \sigma_n^2 + \mathcal{D})^2 - 4\lambda_L\mathcal{D}}}{2\lambda_L}. \tag{17}$$

When $\mathbf{s} = \mathbf{q}_L$ *and* $c = c^{opt}$*, the output SINR is maximized to*

$$SINR_{max}(\mathbf{q}_L, c^{opt}) = \frac{\mathcal{D} - {c^{opt}}^2\lambda_L}{\lambda_L\left(1 - c^{opt}\right)^2 + \sigma_n^2} \tag{18}$$

and maximum SINR data filtering simplifies to $\mathbf{w}_{maxSINR}^T\mathbf{y} \equiv \mathbf{q}_L^T\mathbf{y}$. □

Proposition 4 shows that the optimum signature assignment is still the "minimum" eigenvector of $\mathbf{R}_x$ and maximum SINR filtering still reduces to plain signature (eigenvector) matched filtering. The optimum selection for c depends on the minimum eigenvalue of $\mathbf{R}_x$, λ_L, noise variance σ_n^2, and induced distortion level $\mathcal{D}$. The optimum pair $(\mathbf{s}^{\text{opt}}, c^{\text{opt}})$ allows the output SINR to attain its maximum possible value $\frac{\mathcal{D} - {c^{\text{opt}}}^2}{\lambda_L(1 - c^{\text{opt}})^2 + \sigma_n^2}$.

If we assume that $\mathbf{x}$ is Gaussian, $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_x)$, then $\hat{b} = \text{sign}\left(\mathbf{w}_{\text{maxSINR}}^T\mathbf{y}\right)$ is the optimum bit detector with probability of error $P_e = Q\left(\sqrt{\text{SINR}_{\text{max}}(\mathbf{s}, c)}\right)$. The pair $(\mathbf{s}^{\text{opt}} = \mathbf{q}_L, c = c^{\text{opt}})$ that maximizes the SINR of the maximum SINR filter is the one that also minimizes the probability of error of the optimum detector. The details are given in the following proposition.

Proposition 5 *Consider additive SS embedding according to (12) with* $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_x)$*. Let* $\mathbf{q}_1, \mathbf{q}_2, \cdots, \mathbf{q}_L$ *be eigenvectors of* $\mathbf{R}_x$ *with corresponding eigenvalues* $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_L$*. For any watermark induced distortion level* $\mathcal{D}$*, a (signature* $\mathbf{s}$*, parameter* c*) pair that minimizes the probability of error of the optimum bit detector is*

$$\mathbf{s}^{opt} = \arg\min_{\mathbf{s}}\left\{Q\left(\sqrt{SINR_{max}(\mathbf{s}, c)}\right)\right\} = \mathbf{q}_L \tag{19}$$

and $c^{opt} = \arg\min_{c}\left\{P_e(\mathbf{s}^{opt}, c)\right\}$

$$= \frac{\lambda_L + \sigma_n^2 + \mathcal{D} - \sqrt{(\lambda_L + \sigma_n^2 + \mathcal{D})^2 - 4\lambda_L\mathcal{D}}}{2\lambda_L}. \tag{20}$$

When $\mathbf{s} = \mathbf{q}_L$ *and* $c = c^{opt}$*, the probability of error of the optimum detector is minimized to*

$$P_{e_{min}}(\mathbf{q}_L, c^{opt}) = Q\left(\sqrt{\frac{\mathcal{D} - {c^{opt}}^2\lambda_L}{\lambda_L\left(1 - c^{opt}\right)^2 + \sigma_n^2}}\right) \tag{21}$$

and optimum detection reduces to $\hat{b} = sign(\mathbf{q}_L^T\mathbf{y})$. □

Proposition 5 implies that the "minimum" eigenvector of the host data autocorrelation matrix when used as the embedding signature together with c^{opt} send the probability of error to its minimum possible value $Q\left(\sqrt{\frac{\mathcal{D} - {c^{\text{opt}}}^2\lambda_L}{\lambda_L(1 - c^{\text{opt}})^2 + \sigma_n^2}}\right)$ (conversely, the induced distortion $\mathcal{D}$ is minimized for a given target probability of error P_e).

We can show that for Gaussian host data $\mathbf{x}$ the covert channel capacity is given by

$$C = \frac{1}{2}\log\det\left(\mathbf{I}_L + \left(\mathcal{D} - c^2\mathbf{s}^T\mathbf{R}_x\mathbf{s}\right)\left(\left(\mathbf{I}_L - c\mathbf{s}\mathbf{s}^T\right)\mathbf{R}_x\left(\mathbf{I}_L - c\mathbf{s}\mathbf{s}^T\right) + \sigma_n^2\mathbf{I}_L\right)^{-1}\mathbf{s}\mathbf{s}^T\right). \tag{22}$$

Then, we can prove that the (signature $\mathbf{s}$, parameter c) assignment of Proposition 5 is also optimal in terms of capacity. This result is summarized in the following, last proposition in this paper.

Proposition 6 *Consider additive SS embedding in transformed host data according to (12) with* $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_x)$*. Let* $\mathbf{q}_1, \mathbf{q}_2, \cdots, \mathbf{q}_L$ *be eigenvectors of* $\mathbf{R}_x$ *with corresponding eigenvalues* $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_L$*. For any watermark induced distortion level* $\mathcal{D}$*, a (signature* $\mathbf{s}$*, parameter* c*) pair that maximizes the covert channel capacity is*

$$\mathbf{s}^{opt} = \arg\max_{\mathbf{s}} \Big\{ \frac{1}{2} \text{logdet} \Big(\mathbf{I}_L + (\mathcal{D} - c^2 \mathbf{s}^T \mathbf{R}_x \mathbf{s}) \Big((\mathbf{I}_L - c\mathbf{s}\mathbf{s}^T) \mathbf{R}_x (\mathbf{I}_L - c\mathbf{s}\mathbf{s}^T) + \sigma_n^2 \mathbf{I}_L \Big)^{-1} \mathbf{s}\mathbf{s}^T \Big) \Big\} = \mathbf{q}_L \tag{23}$$

and $$c^{opt} = \frac{\lambda_L + \sigma_n^2 + \mathcal{D} - \sqrt{(\lambda_L + \sigma_n^2 + \mathcal{D})^2 - 4\lambda_L \mathcal{D}}}{2\lambda_L}. \tag{24}$$

When $\mathbf{s} = \mathbf{q}_L$ *and* $c = c^{opt}$*, the covert channel capacity is maximized to*

$$C(\mathbf{q}_L, c^{opt}) = \frac{1}{2} \left(1 + \frac{\mathcal{D} - c^{opt2} \lambda_L}{\lambda_L (1 - c^{opt})^2 + \sigma_n^2} \right) \tag{25}$$

information bits per embedding attempt. □

5. NUMERICAL AND SIMULATION STUDIES

We consider as an illustration vehicle the widely used in the pertinent literature gray-scale 256×256 "Baboon" image. We carry out 8×8 block DCT spread-spectrum embedding over all bins except the dc coefficient; hence, we use embedding signatures of length $L = 63$ and we embed $\frac{256^2}{8^2} = 1,024$ bits. In all studies, we incorporate additive white Gaussian noise of variance $\sigma_n^2 = 3$dB.

In Figs. 1 and 2 we plot the probability of error and Shannon capacity, respectively, of four different system designs as a function of the host image distortion: *(a)* Arbitrary selection of the signature $\mathbf{s}$ with no transformation on the host data ($c = 0$), *(b)* arbitrary selection of the signature $\mathbf{s}$ with optimal selection of the host-data transformation parameter c as in [5] (known as "improved spread-spectrum" or ISS), *(c)* our own optimum selection of the signature $\mathbf{s}$ with no transformation on the host data ($c = 0$), and *(d)* jointly optimum selection of the signature $\mathbf{s}$ and transformation parameter c according to our second proposal. For each design a signature matched filter receiver is utilized. The demonstrated bit error rate and capacity improvements of the proposed schemes -especially the joint signature and projection parameter optimization approach- measure in orders of magnitude.

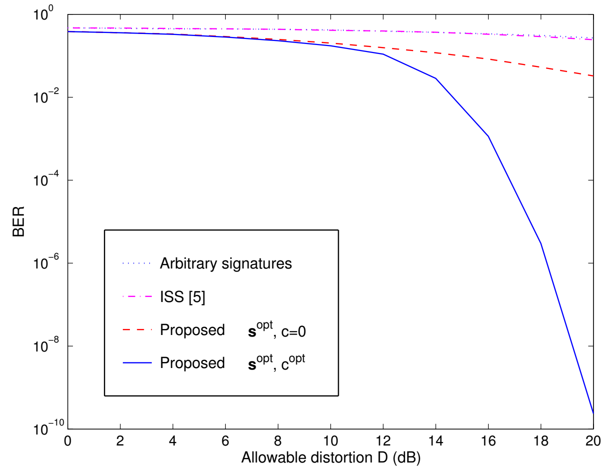

Fig. 1. BER versus host distortion simulation results (Baboon image, $\sigma_n^2 = 3$dB).

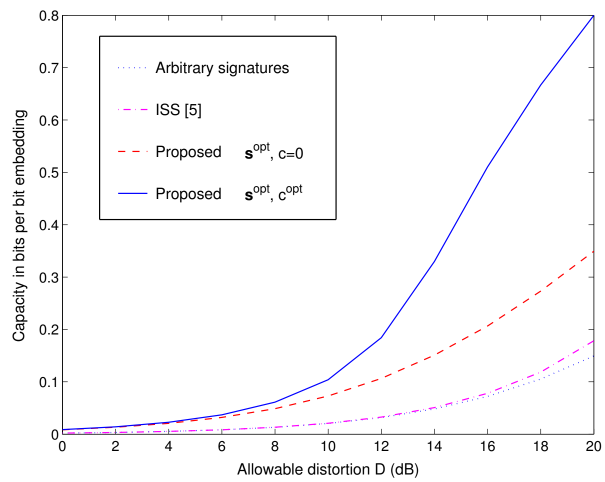

Fig. 2. Capacity versus distortion (Baboon image, $\sigma_n^2 = 3$dB).

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