A New Spatial Steganographic Scheme by Modeling Image Residuals with Multivariate Gaussian Model

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Objectives

This model-driven steganographic scheme is inspired by MG (multivariate Gaussian model)[4] and MiPOD (minimizing the power of optimal detector)[8]. This scheme is based on multivariate Gaussian model of image residuals, instead of pixels in MG. This scheme is abbreviated as MGR. And, this scheme estimates variances by using a simple method instead a complex one in MiPOD.

- Image residuals are obtained by filtering an image with high-pass filters.
- Steganalysis benefits from extracting effective features from image residuals. Modeling image residuals, we aim to better preserve the statistical model of an image.
- Model image residuals as zero-mean quantized multivariate Gaussian distributions. The distribution of stego image residuals can be approximately derived from the embedding change probabilities associated with pixels.
- Fisher information (FI) can be efficiently obtained by using the estimated local variance of residuals and the corresponding high-pass filter coefficients. We select the optimal FI from a set of FIs.
- The proposed scheme performs well and has low computation complexity.

Proposed Method

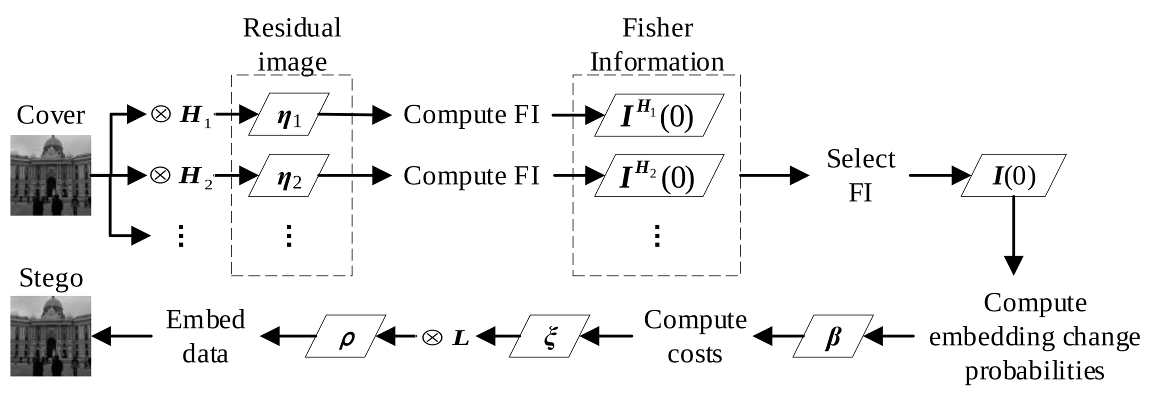

Figure 1: The processing pipeline of the proposed MGR scheme.

1. Residual model
- Let $\mathbf{Y} = \mathbf{X} + \mathbf{N}$, where $\mathbf{X}$, $\mathbf{Y}$ and $\mathbf{N}$ are the cover image, the stego image and the embedding changes, respectively. Image residuals are obtained as :

$$\eta_{\boldsymbol{Y}} = \boldsymbol{Y} \otimes \boldsymbol{H} = (\boldsymbol{X}+\boldsymbol{N}) \otimes \boldsymbol{H} = \eta_{\boldsymbol{X}} + \boldsymbol{N} \otimes \boldsymbol{H}. \quad (1)$$

- The 2-D high-pass filter is formed as :

$$\boldsymbol{H} = \begin{bmatrix} a_{11} & \cdots & a_{1S} \\ \cdots & \cdots & \cdots \\ a_{R1} & \cdots & a_{RS} \end{bmatrix}, a_{uv} \in \mathbb{Z}, \sum_{u=1}^{R}\sum_{v=1}^{S} a_{uv} = 0. \quad (2)$$

- Model residuals as zero-mean quantized multivariate Gaussian distributions $\eta_{X_i} \sim Q_\Delta(\mathcal{N}(0,\nu_i))$. Let the symbols $p^{(i)} = \{p_j^{(i)}\}$ and $q^{(i)} = \{q_j^{(i)}\}$ $(j \in \mathcal{M})$ to denote the probability mass function (PMF) of η_{X_i} and that of η_{Y_i}, respectively.

$$q_j \approx (1-2\beta_i)p_j + \frac{\beta_i}{R\times S}\sum_{u=1}^{R}\sum_{v=1}^{S}(p_{j+a_{uv}} + p_{j-a_{uv}}). \quad (3)$$

- For a large n and small embedding change probabilities β_i, the total KL divergence between the cover and the stego can be approximated by :

$$\sum_{i=1}^{n} D_{KL}(p^{(i)}||q^{(i)}) = \frac{1}{2}\sum_{i=1}^{n}\beta_i^2 I_i(0). \quad (4)$$

- The FI is approximate as :

$$I_i(0) = \sum_j \frac{1}{p_j^{(i)}}\left(\frac{\partial q_j^{(i)}}{\partial \beta_i}\Big|_{\beta_i=0}\right)^2 \approx \frac{\Delta^4(\sum_{u=1}^{R}\sum_{v=1}^{S} a_{uv}^2)^2}{(R\times S)^2\nu_i^2}. \quad (5)$$

The FI is relative to v_i^2 of residuals and coefficients of the filter.

2. Computing Costs
- The final FI values are obtained by $I_i(0) = \max\{I_i^{\boldsymbol{H}_k}(0)\}, \boldsymbol{H}_k \in \mathbb{H}$.
- Under payload constraint $\alpha n = \sum_{i=1}^{n} h(\beta_i)$, compute change probabilities β_i.
- Satisfying $\beta_i = exp(\lambda\xi_i)/(1+2exp(\lambda\xi_i))$, the initial costs are solved as :

$$\xi_i = \frac{1}{\lambda}\ln(\frac{1}{\beta_i} - 2). \quad (6)$$

- Use an average low-pass filter to spread the initial costs to obtain the final embedding costs as :

$$\boldsymbol{\rho} = \boldsymbol{\xi} \otimes \boldsymbol{L} \quad (7)$$

Experiments

1. Setup.
- Database : BOSSBase ver.1.01[1].
- Comparison schemes
  - Designed heuristically : WOW[5], S-UNIWARD[6] and HILL[7]
  - Model-based : MG[4] and MiPOD[8]
- Steganalysis
  - Artificial features : SRM[3] and maxSRMd2[2]
  - Deep neural network : Xu-Net[9]
- The ternary optimal embedding simulator was used for all methods.

2. Impact of parameters.

Table 1: $\overline{P}_E$ of MGR with different high-pass filters under different payload α against SRM. MGR* denotes the scheme using SH, SV, and KB filters together. (MG is used for comparison.)

α	0.05	0.1	0.2	0.3	0.4	0.5
MG	0.3715	0.2935	0.2131	0.1654	0.1339	0.1119
MGR(SH)	0.4083	0.3467	0.2686	**0.2142**	**0.1733**	**0.1400**
MGR(KB)	**0.4327**	**0.3668**	**0.2745**	0.2066	0.1617	0.1253
MGR(KV)	0.4155	0.3511	0.2485	0.1884	0.1443	0.1129
MGR*	0.4516	0.3951	0.3081	0.2383	0.1882	0.1518

Table 2: $\overline{P}_E$ of MGR* with $h\times h$ average filter under different payloads α against SRM.

α	0.05	0.1	0.2	0.3	0.4	0.5
$h=3$	0.4584	0.4108	0.332	0.2741	0.2193	0.1782
$h=5$	0.4653	**0.4296**	0.358	0.2961	0.2473	0.2020
$h=7$	**0.4668**	0.4289	**0.3624**	**0.3015**	**0.2506**	**0.2103**
$h=9$	0.4644	0.4276	0.3587	0.2991	0.2488	0.2079
$h=11$	0.4613	0.4258	0.3565	0.2974	0.2463	0.2065

3. Comparison to Existing Methods. (MGR is MGR* with $h=7$.)

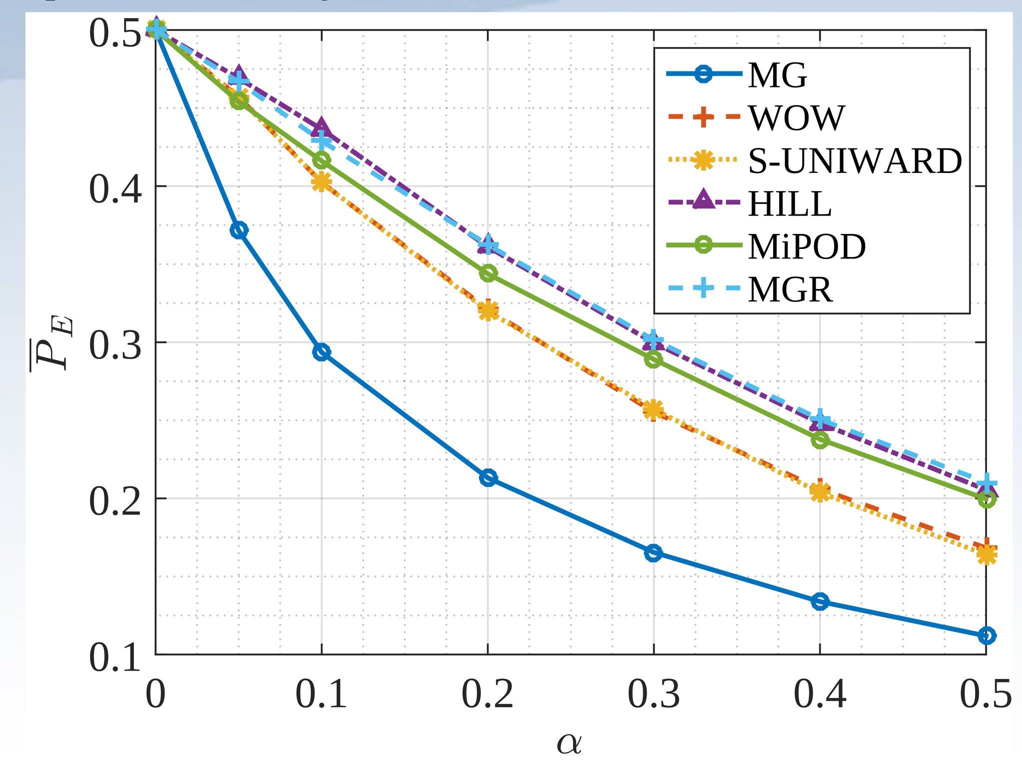

Figure 2: Against SRM.

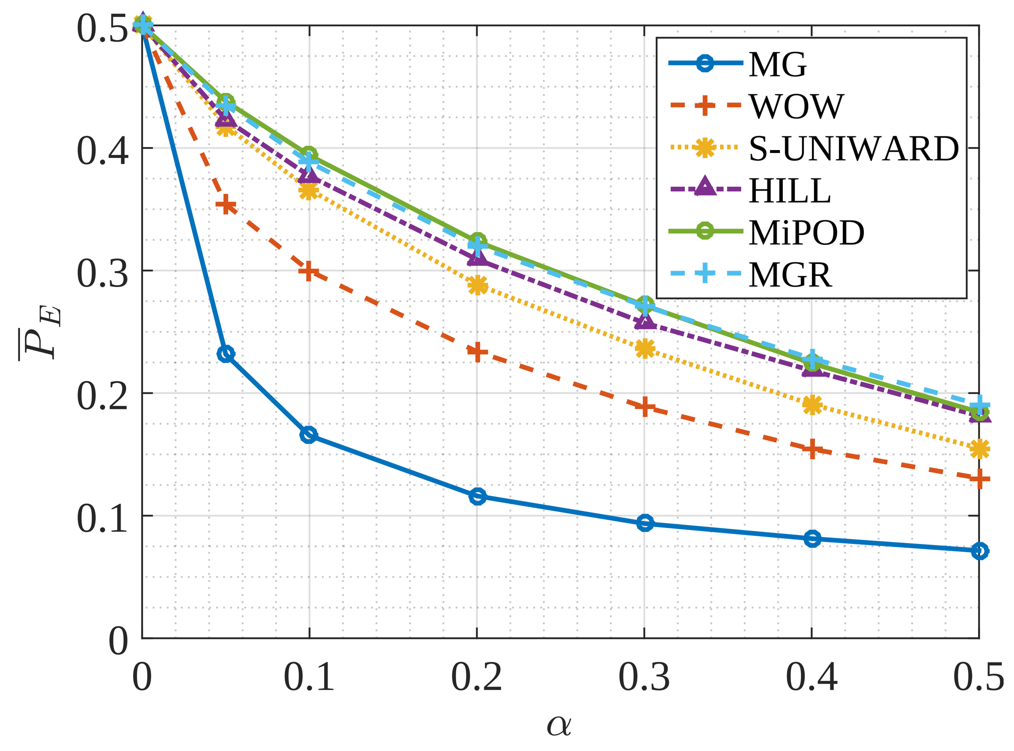

Figure 3: Against maxSRMd2.

Table 3: $\overline{P}_E$ under different payloads α against Xu-Net.

α	0.05	0.1	0.2	0.3	0.4	0.5
HILL	**0.4622**	0.4072	0.3352	0.2751	0.2259	0.1963
MiPOD	0.4591	0.4117	0.3359	0.2730	0.2306	0.1945
MGR	0.4595	**0.4251**	**0.3540**	**0.2908**	**0.2478**	**0.2073**

4. Computation complexity

Table 4: The averaged elapsed time (in second) used in computing FI for MiPOD and MGR.

Scheme	MiPOD	MGR
Elapsed time (s)	0.4329	**0.0542**

Conclusion

- Different from MG which models image elements, MGR explicitly considers the KL divergence in terms of image residuals, which are commonly used in steganalysis.
- The mathematically derived FI is related to both Gaussian variance and high-pass filter coefficients.
- Various filters can be employed in MGR by considering the maximum FI values.
- The proposed method achieves the best overall performance when compared with HILL and MiPOD.

Future Research

Take more insightful investigation such as making regulation on the filter coefficients to improve performance.

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