Color Image Steganalysis
Based on Steerable Gaussian Filters Bank

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Steganography / Steganalysis

Alice → Cover image C → Emb → Stego image S → Ext → Bob

Message M

Stego ≈ Cover

Secret key K

Eve

Steganography is the art and science of hiding messages in such a way that the carrier appears to be innocent. Steganalysis is the study of methods for recovering information that has been hidden in the carrier, which may be a cover image or other carrier.
Color steganalysis

Few dates and references

- 2013, The color steganography / steganalysis could be explored (a real world problem) [14],
- 2014, The CFA traces can be used: [15], CFARM [9],
- 2015, The correlation between color channels can be used: CRM [10], GCRM [2].


15 ”Steganalysis in technicolor” boosting ws detection of stego images from CFA-interpolated covers, ” M. Kirchner and R. Bohme, ICASSP’2014, Florence, Italy, May 2014.


Proposition

In the rich model method, a residual is computed for each pixel:

\[ R(x, y) = \hat{I}(x, y)(N(x, y)) - c \cdot I(x, y). \]

Proposition

- Define the residual as a function of a gradient and a tangent,
- \( \rightarrow \) Use more precise filters than those used in SRM.

Remark: The proposition may also be applied to grey-level images.
Why using Steerable Gaussian Filters?

The facts...

- Filters bank allows to better detect image features such as edges,
- The steerable filters are one of the most popular solution,
- Freeman and Adelson [5] have proposed steerable filters directed at specific angles built with a linear combination of Gaussian derivatives.

→ A finer computation of magnitude of the gradient and the tangent!

Definition of the Steerable Gaussian Filters (1)

Let us note the basic derivatives of Gaussian filters $\partial G_\sigma / \partial x$ and $\partial G_\sigma / \partial y$ along the $x$-axis and $y$-axis at position $(x, y)$ in the image:

\[
\begin{align*}
\frac{\partial G_\sigma(x, y)}{\partial x} &= -\frac{x}{2\pi \sigma^4} \cdot e^{-\frac{x^2 + y^2}{2\sigma^2}}, \\
\frac{\partial G_\sigma(x, y)}{\partial y} &= -\frac{y}{2\pi \sigma^4} \cdot e^{-\frac{x^2 + y^2}{2\sigma^2}},
\end{align*}
\]

with $\sigma$ the standard-deviation of the Gaussian filter.
Definition of the Steerable Gaussian Filters (2)

The first order directional Gaussian derivative $G_{\sigma, \theta}$ at an angle $\theta$ can be expressed as [5]:

$$G_{\sigma, \theta}(x, y, \sigma) = \cos(\theta) \cdot \frac{\partial G_{\sigma}}{\partial x}(x, y) + \sin(\theta) \cdot \frac{\partial G_{\sigma}}{\partial y}(x, y).$$  \hspace{1cm} (2)

→ Possible to build a filter kernel for a given angle $\theta$
→ ... then to apply a convolution and to find the derivative for that angle.
Illustration (1): A Steerable Gaussian Kernel

A kernel with $\theta_m$ its kernel angle.
Illustration (2): Steerable Gaussian Kernels

- $\sigma = 0.7$, filter support size $= 3 \times 3$ pixels,
- Rotation step $= \Delta \theta = 10^\circ$,
- Rotation range $= \theta \in \{0^\circ, \ldots, 180^\circ - \Delta \theta\}$,
- Leads to 18 filters (Dresden and BOSSBase, PPM demosaicking, and cropping)
Definition of the Steerable Gaussian Filters (3)

Given $\sigma$ and $\theta$, an image derivative $I_{\sigma,\theta}$ is obtained by convolving the original gray-scale image $I$ with the oriented Gaussian kernels $G_{\sigma,\theta}$:

$$I_{\sigma,\theta}(x,y) = (I \ast G_{\sigma,\theta})(x,y).$$  \hspace{1cm} (3)

The gradient magnitude $\|\nabla I(x,y)\|$ equals to the maximum absolute value response of $G_{\sigma,\theta}$ for the different angles:

$$\|\nabla I(x,y)\| = \max_{\theta \in [0,180]} (|I_{\sigma,\theta}(x,y)|),$$  \hspace{1cm} (4)

$$\theta_m = \arg\max_{\theta \in [0,180]} (|I_{\sigma,\theta}(x,y)|) .$$  \hspace{1cm} (5)

$\theta_m$ is the kernel angle.
An interesting complementary measure

A fact...

- The modifications due to embedding will preferentially occur along the curves of constant intensity.

→ Let us also consider the tangent vector
... that is to say the derivative value at angle \((\theta_m + 90^\circ) [180^\circ]\)
For a color image, each channel is considered separately.

A gradient magnitude per channel ($|R_{\sigma,\theta_m}|$ for the red, and so on...)

A tangent derivative per channel ($R_{\sigma,(\theta_m+90)[180^\circ]}(x,y)$ ...)

Then,

- quantize,
- truncate,
- compute triplets co-occurrence matrices for directions $\in \{\rightarrow, \leftarrow, \uparrow, \downarrow, \nearrow, \swarrow, \nwarrow, \searrow\}$,
- and apply a SPAM merging process.
Features: "Steerable Gaussian - Color Rich Model (SGRM)"

Our SGRM features are made of:

- 18 157 features from CRM [10],
- 2 808 features from gradient magnitude images ($T \in \{2, 3\}$),
- 1 598 features from tangent derivative images ($T \in \{1, 2, 3\}$ and for $T=3$ there is a fusion of matrices),

Feature vector dimension = 22 563.

Experimental Protocol

10,000 color images of size $512 \times 512$:

- 3,500 Nikon Raw Color images from Dresden Image Database,
- 1,000 Canon Raw color images from Break Our Steganographic System Database,
- Patterned Pixel Grouping (PPM) demosaicking,
- Randomly cropped images (the left-up pixel has a non interpolated Red value) of size $512 \times 512$.

Embedding algorithms:

- S-UNIWARD,
- WOW,
- Synch-HILL,

Payload sizes $\in \{0.01, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5\}$ Bit Per Channel,

Same proportion in each channel.
Performance Evaluation

We use the testing error under equal priors:

\[ \bar{P}_E = \min_{P_{FA}} \frac{1}{2} [P_{FA} + P_{MD}(P_{FA})] , \]

with \( P_{FA} \) the false alarm probability, and \( P_{MD} \) the missed detection probability.

- 10 different splits with 10 000 pairs of covers/stegos for the learning and for the test,
- The Ensemble Classifier for learnings/tests,
- \( \bar{P}_E \) is the average testing error over 10 tests.
Results: S-UNIWARD

![Graph showing the probability of error $P_E$ against relative payload (bpc) for different methods including CRM, CFARM, GCRM, and the proposed method.]
Results: WOW

![Graph showing the probability of error $P_E$ vs. relative payload (bpc) for different methods: CRM, CFARM, GCRM, and Proposed method. The graph illustrates how the proposed method performs compared to the others.](image-url)
Results: Synch-HILL
Discussion

- A fine estimation of the gradient magnitude and the derivate for the tangent increases the detection of 2-3% compared to CRM.
- This is the most efficient approach among the modern approaches whose feature vector dimensions $\approx 20\,000$,
- The concatenation of GCRM and SGRM does not significantly improve the results ($<1\%$),
Conclusion

- Steerable Gaussian Filter for a precise estimation of gradients and tangents,
- The feature set is added to the CRM set,
- The best results for color steganalysis on a color database whose RAW images have been demosaicked with PPM.

- Some trivial additional tests (color or not) can be done,
- Open issues for color steganography:
  - embedding with a global optimized approach,
  - a MiPOD-like embedding?
  - synchronization of the selection channel (see [23] CMD-Color),
  - JPEG and color (color space, sampling, quantization,...)
- Open issues for color steganalysis:
  - How to better take into account the correlation between channels?,
  - What are the results with an Adaptive steganalysis (Selection-Channel-Aware steganalysis)?