# Color Image Steganalysis
# Based on Steerable Gaussian Filters Bank

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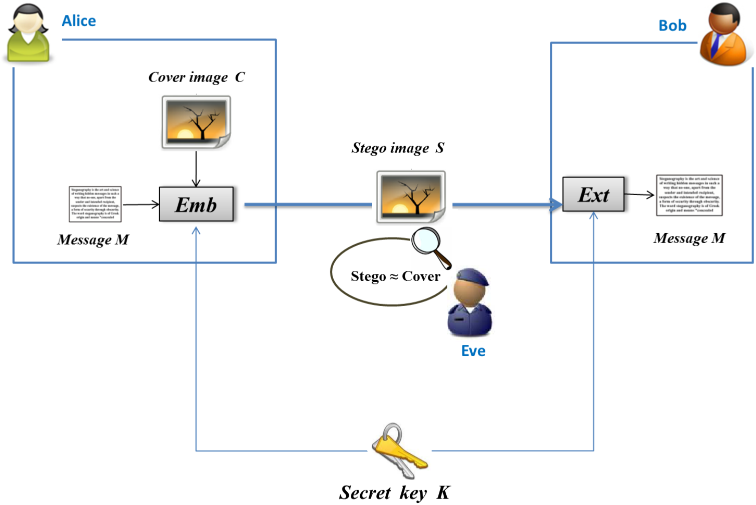
# Steganography / Steganalysis



# 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].


14 Real World: " Moving steganography and steganalysis from the laboratory into the real world, " A. D. Ker, P. Bas, R. Böhme, R. Cogranne, S. Craver, T. Filler, J. Fridrich, and T. Pevnỳ, IH&MMSec'2013, Montpellier, France, June 17-19, 2013.

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.

9 CFA Rich Model (CFARM): " CFA-aware features for steganalysis of color images, " M. Goljan and J. Fridrich, IS&T/SPIE Electronic Imaging 2015, San Francisco, CA, USA, Feb. 2014.

10 Color Rich Model (CRM): " Rich model for steganalysis of color images, " M. Goljan, J. Fridrich, and R. Cogranne, WIFS'2014, Atlanta, GA, USA, Dec. 2014.

2 Geometric Rich Model (GRM): " Color images steganalysis using rgb channel geometric transformation measures, " H. Abdulrahman, M. Chaumont, P. Montesinos, and B. Magnier, Wiley Journal, Feb. 2016.

# Proposition

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

$$\mathbf{R}(x, y) = \hat{I}(x, y)(\mathcal{N}(x, y)) - c \cdot I(x, y).$$

## 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!

[5] W. T. Freeman and E. H. Adelson, " The design and use of steerable filters, " in IEEE Trans. on Pattern Analysis & Machine Intelligence, Vol.13(9):pp.891–906, 1991.

# Definition of the Steerable Gaussian Filters (1)

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

$$\begin{cases} \dfrac{\partial\mathcal{G}_\sigma(x,y)}{\partial x} & = \dfrac{-x}{2\pi\sigma^4} \cdot e^{-\dfrac{x^2+y^2}{2\sigma^2}} \\ \dfrac{\partial\mathcal{G}_\sigma(x,y)}{\partial y} & = \dfrac{-y}{2\pi\sigma^4} \cdot e^{-\dfrac{x^2+y^2}{2\sigma^2}}, \end{cases} \quad (1)$$

with $\sigma$ the standard-deviation of the Gaussian filter.

# Definition of the Steerable Gaussian Filters (2)

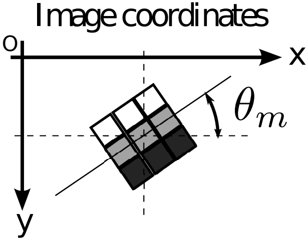
The first order directional Gaussian derivative $\mathcal{G}_{\sigma,\theta}$ at an angle $\theta$ can be expressed as [5]:

$$\mathcal{G}_{\sigma,\theta}(x, y, \sigma) = \cos(\theta) \cdot \frac{\partial \mathcal{G}_\sigma}{\partial x}(x, y) + \sin(\theta) \cdot \frac{\partial \mathcal{G}_\sigma}{\partial y}(x, y). \tag{2}$$

$\rightarrow$ Possible to build a filter kernel for a given angle $\theta$
$\rightarrow$ ... then to apply a convolution and to find the derivative for that angle.

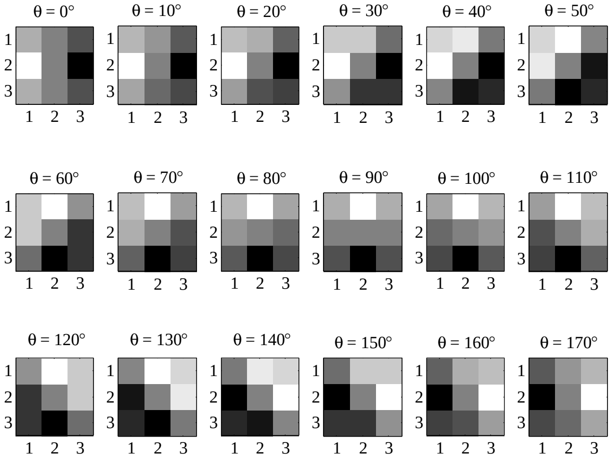
# Illustration (1): A Steerable Gaussian Kernel

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 $= \theta \in \{0^\circ, ..., 180^\circ - \Delta\theta\}$,
- 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 $\mathcal{G}_{\sigma,\theta}$:

$$I_{\sigma,\theta}(x,y) = (I * \mathcal{G}_{\sigma,\theta})(x,y). \quad (3)$$

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

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

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

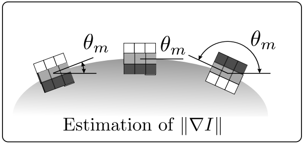
$\theta_m$ is the *kernel angle*.

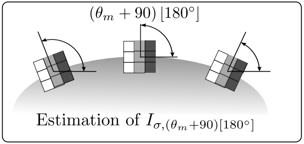
# An interesting complementary measure

## A fact...

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

$\rightarrow$ Let us also consider the tangent vector
... that is to say the derivative value at angle $(\theta_m + 90°)\ [180°]$



# Resume

- 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-occurence 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.

[10] M. Goljan, J. Fridrich, and R. Cogranne., " Rich model for steganalysis of color images, " in Proc. IEEE Int. Workshop on Inf. Forensics Security, Atlanta, GA, USA, pages 185–190, Dec. 2014.

# Experimental Protocol

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

- 3500 Nikon Raw Color images from Dresden Image Database,
- 1000 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

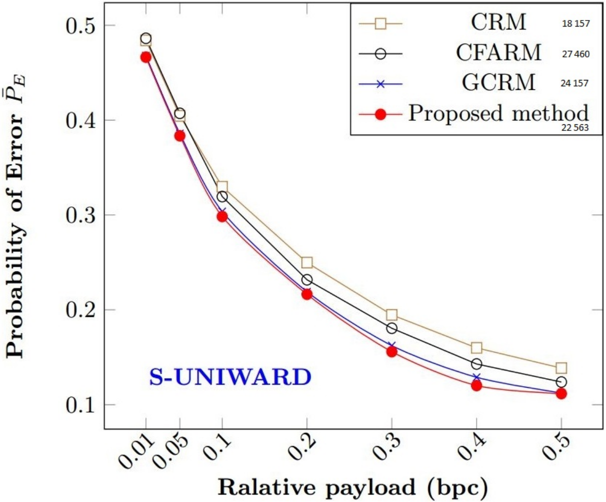
We use the testing error under equal priors:

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

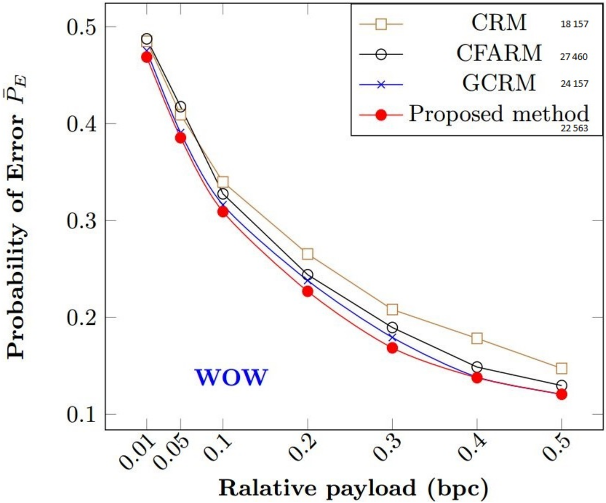
with $P_{FA}$ the false alarm probability, and $P_{MD}$ the missed detection probability.

- 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

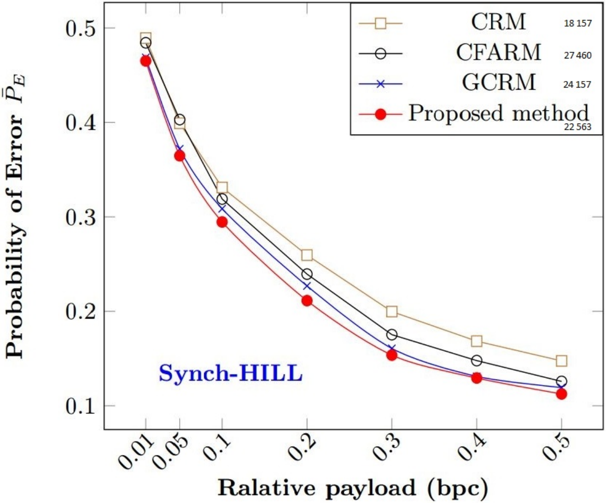


# Results: WOW



CRM 18 157
CFARM 27 460
GCRM 24 157
Proposed method 22 563
WOW
Probability of Error $\bar{P}_E$
0.1
0.2
0.3
0.4
0.5
0.01
0.05
0.1
0.2
0.3
0.4
0.5
Ralative payload (bpc)

# 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 demoisaicked 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)?