



Steganographic Capacity of Images, based on Image Equivalence Classes

by

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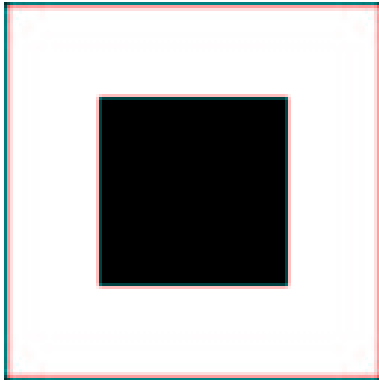
This work is partly based on a Master's thesis by Christian Hammer and Lars R. Randleff at the Department of Computers Science, University of Copenhagen, 2000.

The slides were made using the \LaTeX and Utopia system.

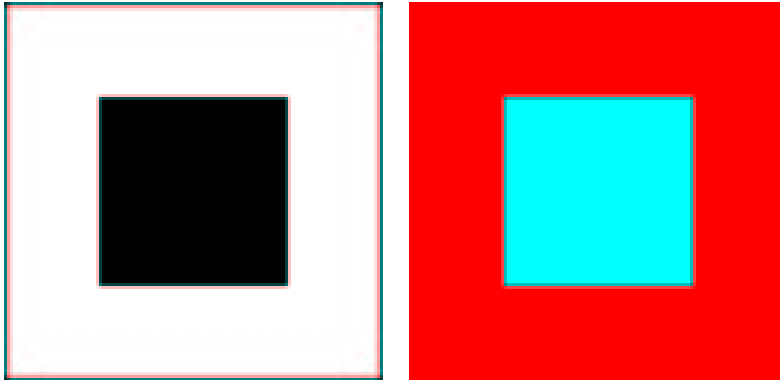
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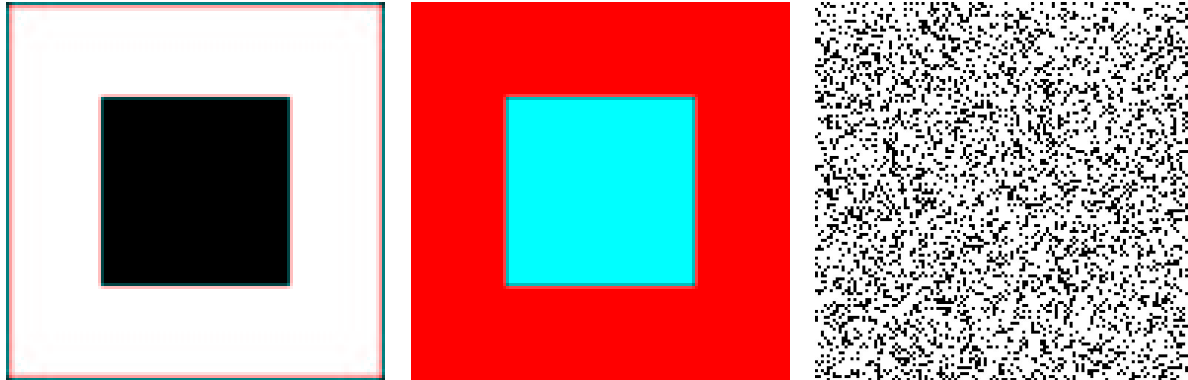
What is the capacity of a given image?



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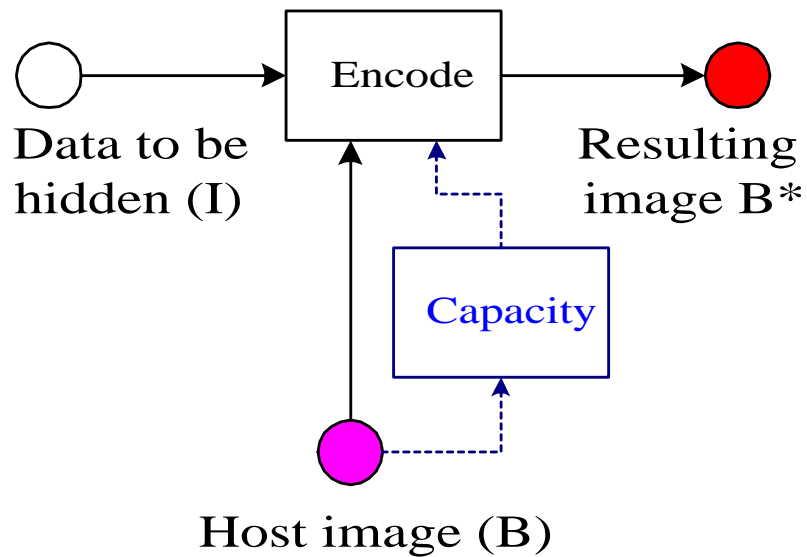
What is the capacity of a given image?



Do all images have capacity?

- Some images have zero capacity
 - ◇ efficiently compressed images
 - ◇ no data manipulation a user requirement
- Capacity depends on the visual quality level for the application area

Information hiding model



The modification by the encoding process should be invisible or nearly undetectable. The data to be hidden may be a fragile verification seal or a robust proof of ownership/restrictions on use.

Coding

- Hiding corresponds to transmission over a noisy channel, but the noise is not Gaussian
- Channel states (constellation patterns), each coding a multi-bit value, maps to specific manipulations of the host image
- The actual coding (spatial domain, frequency domain) will not be treated here

Steganographic capacity [1]

Ross Anderson [1996]: if E is data to be hidden and M is the set of allowable host images, the data can be hidden if $H(M) < H(E)$, where $H()$ is the entropy

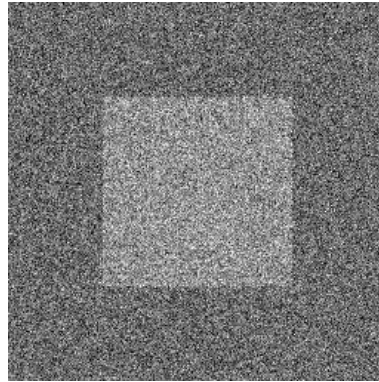
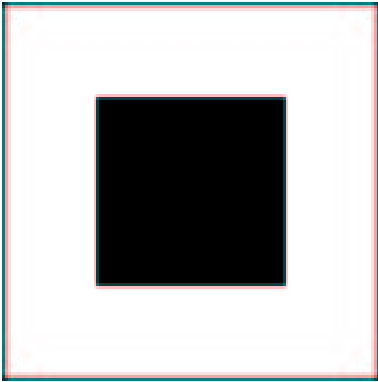
We however have some problems using entropy.

Steganographic capacity [2]

Problems:

- $H()$ is a statistical measure, which do not take the properties of the HVS (Human Visual System) and application specific requirements into account
- How do we define and measure $H(B)$ for a given single image?

Entropy



What is the entropy of these images? Do they have capacity for hiding data?

Histogram entropy

- The entropy computed from the histogram is not usable, as a huge number of images have the same histogram
- The same histogram may cover images having completely dissimilar structure and appearance

Various approaches

Statistical and information-theoretical characterization of images:

- Combinatorial entropy of images (2D fields) (Buccigrossi)
- Grammars for visual or two-dimensional languages
- Julesz ensembles (Wu)
- Multi-fractal properties (Turiel)

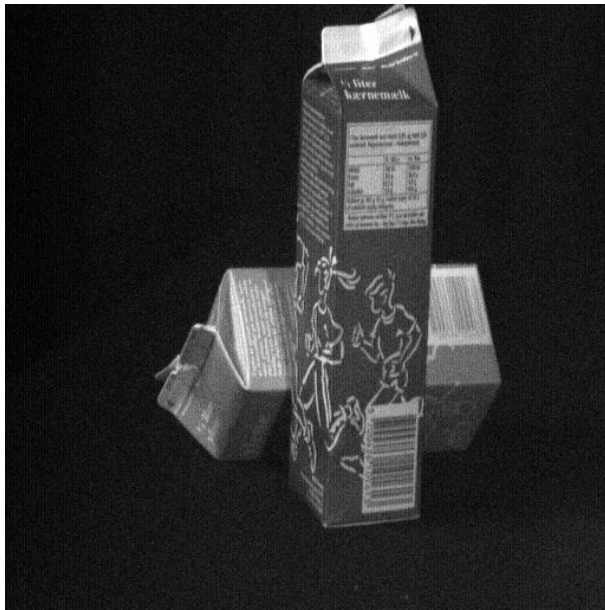
Equivalence classes [1]

- Universe $\mathcal{U}_{M_1, M_2, P}$ of images of size $M_1 \cdot M_2$, having P -bit pixels
- A given image is member of a subset of $\mathcal{U}_{M_1, M_2, P}$ which consists of visibly equivalent images
- Data may be hidden by transforming the host image into another member of the subset
- Julesz ensembles are based on texture parametrization

Entropy estimate derived from combinatorial arguments

We count the number N of images which are structurally closely related. The entropy may be computed as $\log(N)$ if the images are assumed to have the same probability. Noise (additive noise, quantization errors, compression artifacts etc.) is treated separately.

Equivalence classes [2]

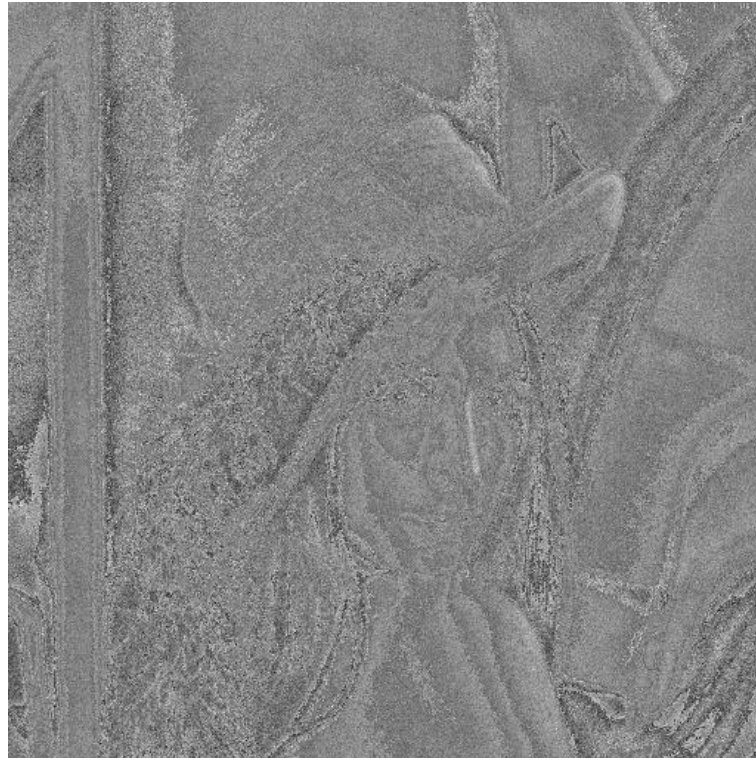


Left image “milk3”; right the amplitude component of Lena has been replaced by the amplitude, keeping the original phase from milk3.

Equivalence classes [3]



The histogram of Lena divided into six partitions. Right all pixel values in each partition have been replaced by values taken from a Gaussian distribution with same mean and variance.



Difference between the original image and the new image on the previous slide

The size of image classes

We do not seek a general measuring algorithm, but a set of algorithms each suited for a specific class of images, e.g.

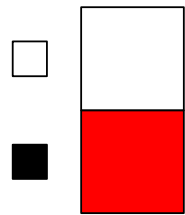
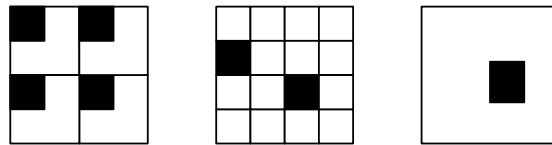
- Indoor or outdoor scenes
- Aerial photographs
- Images from medical scanners, X-ray or ocular fundus images

Three-layer model

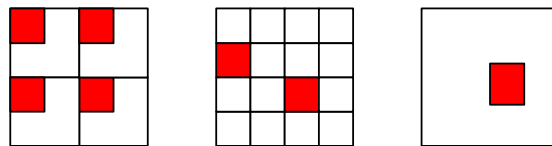
- Universe $\mathcal{U}_{M_1, M_2, P}$ of images of size $M_1 \cdot M_2$, having P -bit pixels
- Image $I_{M_1, M_2, P} \in \mathcal{U}_{M_1, M_2, P}$ has structure S (described by e.g. a 2D grammar)
- Each segment has texture T (which locally depends on $S_i - T | S_i$)
- Stochastic element N (noise etc.), independent of T and S

Structure and texture [1]

Generating
Grammar

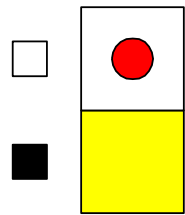
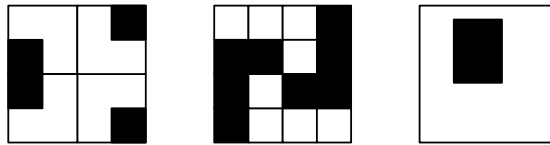


Texture

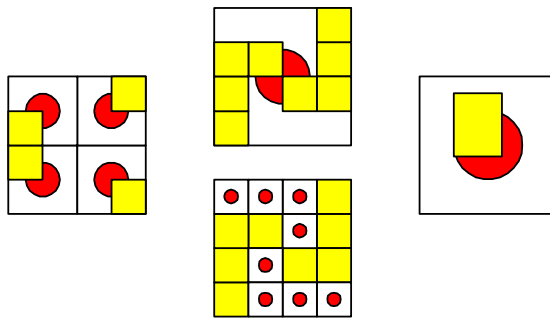


Structure and texture [2]

Generating
Grammar

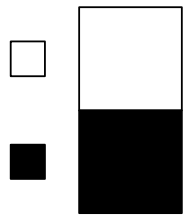
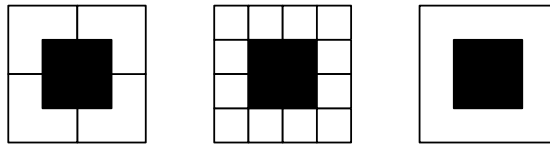


Texture

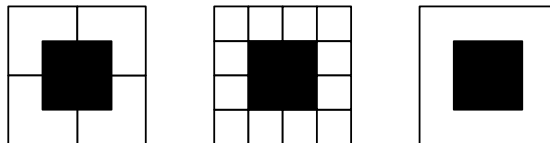


Structure and texture [4]

Generating
Grammar



Texture



Hiding using S , T or N

- Using S is difficult and the capacity is probably very limited
- Using T (by e.g. Julesz ensemble parameters, MRF descriptions or some transformation domain) seems feasible
- Using N is not robust, and not all images have a significant N

Second part