Watermark attacks

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Content

1. Introduction

1.1 Why deal with attacks

Market is lukewarm towards watermarking technology:

- non-disclosed methods;
- no standard, general purpose benchmark;
- lack of robustness to attacks.

(Almost) anybody can break a watermark:

- blind use of simple manipulations;
- after study of the methods.

Why work on attacks:

- develop better methods, as with cryptography;
- define better benchmarks.

Pioneering work: Stirmark (benchmarking), Unzign.

1.2 Goals of watermarking attacks

Notations:

x: original (cover image), size $N = M \cdot M$,
n: noise-like watermark,
y: stego-image, with

$$y = x + n \tag{2.1}$$

y': **attacked** stego-image.

Main goals of attacks on watermarks:

- preserve image quality:

$$y' \cong x \tag{2.2}$$

- render watermark undetectable/undecodable.

Our goal is to use prior knowledge:

- of watermark and image probability distributions;
- of the watermarking method used.

1.3 Families of watermark attacks

Main attack families we are concerned with:

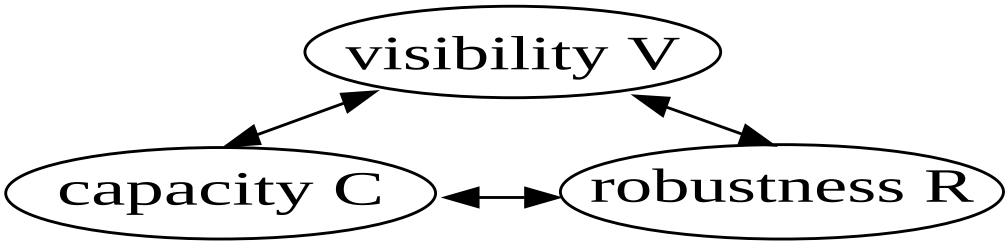
- geometric $\rightarrow$ desynchronization, e.g.:
  - affine transforms;
  - cropping, row/column removal;
  - random local distortions;
  - mosaicing;
- signal processing $\rightarrow$ desynchronization, watermark drowning, e.g.:
  - lossy compression, (re)quantization, dithering;
  - linear, non-linear and adaptive filtering, denoising;
  - multiple watermarks, noise addition;
  - collage, superimposition;
  - **stochastic attacks**;
- specialized, based on knowledge of method:
  - **desynchronization attacks**;
  - chrominance attack;
  - etc.

We ignore here cryptographic attacks, system-based attacks (e.g. Oracle, counterfeit original, averaging).

Stirmak: geometric, signal processing.

1.4 Benchmarking watermarking methods

3 related criteria for watermarking, reflected in the benchmarks:



Visibility V:

- subjective human evaluation;
- HVS-based computer model;
- PSNR:

$$\mathrm{PSNR} = 10\log\frac{\text{max\_luminance\_x}^2}{\|(y-x)\|^2} \tag{2.3}$$

Capacity C: bits, typically 64 .. 100.

Robustness R:

- bit error rate;
- binary decision:
  - watermark detected;
  - watermark not detected.

Stirmark: subjective evaluation, binary answer only.

1.5 Benchmarking watermark attacks

Visibility V:

- subjective human evaluation;
- HVS-based computer model;
- **weighted PSNR** measured on $y' - x$:

wPSNR =

$$10\log\frac{\mathrm{max\_lum\_x}^2}{\|(y' - x)\|_{NVF}^2} = 10\log\frac{\mathrm{max\_lum\_x}^2}{\|(y' - x)\cdot NVF\|^2} \quad (2.4)$$

(e.g. flat region: NVF = 1 $\rightarrow$ max penalization)

Capacity C: given number of bits.

Robustness R:

- bit error rate;
- binary answer:
  - watermark detected;
  - watermark not detected.
- ternary answer:
  - watermark present & detected,
  - watermark present & not detected,
  - watermark not present.

The wPSNR is closer to perception than the PSNR:

stego-image
PSNR 24.6dB
wPSNR 26.4dB

stego-image
PSNR 24.6dB
wPSNR 27.9dB

stego-image
PSNR 24.6dB
wPSNR 29.3dB

2. Stochastic attacks

2.1 Introduction

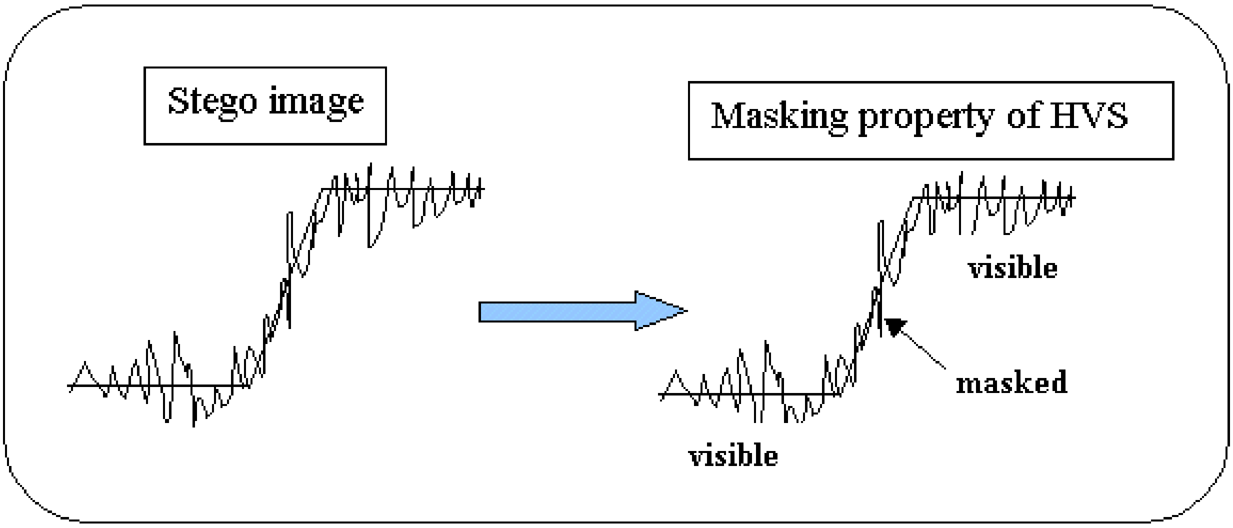
Goal: general attack on watermark schemes.

The attack:

- takes into account **human perception**;
- is **stochastic**: applicable to a wide class of image and video watermarking schemes.

Can be used against embedding schemes operating in coordinate or transform (FT, DCT, wavelets) domains.

Masking property:

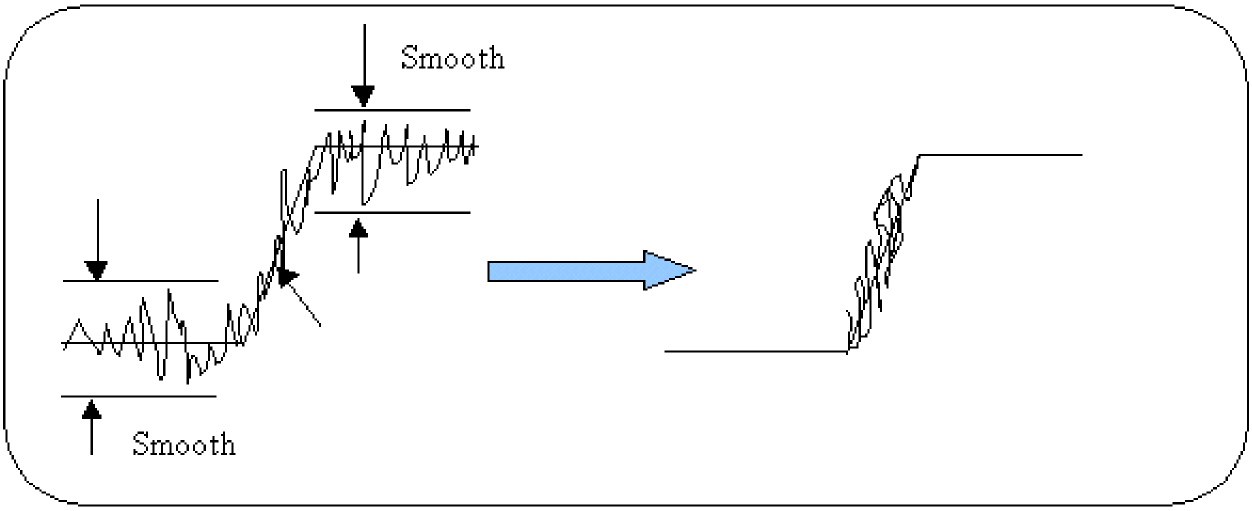


(Details in Information Hiding 1999 paper.)

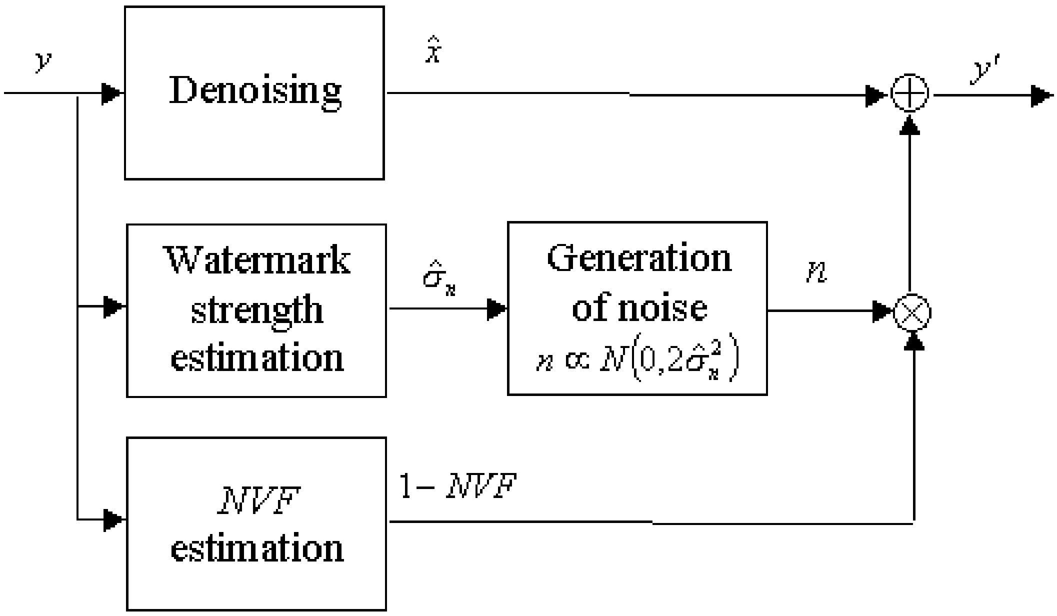
Two stages attack:

- watermark estimation and removal: denoise;
- watermark hiding: add noise, using watermark statistics and HVS properties.

Basic idea:



Implementation:



2.2 Stage 1: watermark estimation

Goal: remove watermark from flat regions.

Watermark:

$$\hat{n} = y - \hat{x}, \tag{2.5}$$

where $\hat{n}, \hat{x}$ are estimates of watermark & cover image.

Assumptions:

- watermark = Gaussian r.v., indep. ident. distributed samples (spread spectrum wm, binary wm + NVF):

$$p_n(n) \propto \text{i.i.d.}\, N(0, I\sigma_n^2) \tag{2.6}$$

- cover image: stationary Generalized Gaussian distribution, i.i.d. samples:

$$p_x(x) \propto \text{i.i.d.}\, GG(\bar{x}, R_x) \tag{2.7}$$

for which the shape parameter γ can vary:

$\gamma = 2$: Gaussian distribution,
$\gamma = 1$: Laplacian distribution,
$0.3 \le \gamma \le 1$: real cover images.

Other possibility: non-stationary Gaussian pdf for cover image (see Information Hiding 1999 paper).

Estimation of $\hat{x}$:

$$\hat{x} = \arg\max\{\ln p_n(y|\tilde{x}) + \ln p_x(\tilde{x})\},\ \tilde{x} \in \Re^N \qquad (2.8)$$

Iterative RLS - Reweighted Least Squares solution:

$$\hat{x}^k \rightarrow \hat{w}^{k+1} \rightarrow \hat{x}^{k+1} \qquad \text{(w: weight)} \qquad (2.9)$$

Resulting formulation, similar to the Lee filter:

$$\hat{x}^{k+1} = \hat{\bar{x}}^k + \frac{\hat{\sigma}^2_{x^k}}{\hat{w}^k\hat{\sigma}^2_n + \hat{\sigma}^2_{x^k}}(y - \hat{\bar{x}}^k) \qquad (2.10)$$

Equivalent form as generalized Wiener filter:

$$\hat{x}^{k+1} = \frac{\hat{w}^k\hat{\sigma}^2_n}{\hat{w}^k\hat{\sigma}^2_n + \hat{\sigma}^2_{x^k}}\hat{\bar{x}}^k + \frac{\hat{\sigma}^2_{x^k}}{\hat{w}^k\hat{\sigma}^2_n + \hat{\sigma}^2_{x^k}}y \qquad (2.11)$$

where for one iteration step k:

- $\hat{\sigma}^2_n$: wm variance estimate, eg. on flat regions;
- $\hat{\sigma}^2_x \rightarrow \hat{\sigma}^2_{x_{i,j}}$, $1 \le i, j \le N$: local img variance estimate;
- $\hat{w}^k(i,j) = \dfrac{\gamma[\eta(\gamma)]^\gamma}{|r^k(i,j)|^{2-\gamma}}$, $\hat{r}(i,j) = \dfrac{\hat{x}(i,j) - \hat{\bar{x}}(i,j)}{\hat{\sigma}_x}$;
- γ: estimated using moment matching;
- $\eta(\gamma) = \sqrt{\Gamma(3/\gamma)/\Gamma(1/\gamma)}$, with Gamma fonction.

2.3 Stage 2: noise addition

Goal: add noise to hide/cancel watermark.

Noise visibility function (assuming noise $N(0, 1)$):

$$\mathrm{NVF}(i, j) = \frac{w(i, j)\sigma_n^2}{w(i, j)\sigma_n^2 + \sigma_x^2} \rightarrow \frac{w(i, j)}{w(i, j) + \sigma_x^2} \qquad (2.12)$$

Behavior:

- flat regions: $\mathrm{NVF} \rightarrow 1$;
- textured regions and edges: $\mathrm{NVF} \rightarrow 0$

Watermark drowning:

$$\begin{aligned} y' = \hat{x} &+ \\ &[1 - \mathrm{NVF}(i, j)] \cdot m(i, j) \cdot S_e + \qquad \text{(edges)} \\ &\mathrm{NVF}(i, j) \cdot m(i, j) \cdot S_f \qquad \text{(flat areas)} \qquad (2.13) \end{aligned}$$

where:

- m: factor used to remodulate the watermark:

$$m(i, j) = -1 \cdot \mathrm{sgn}[\hat{n}(i, j)] \qquad (2.14)$$

- $\hat{n}(i, j)$: estimated from (2.11) and (2.5);
- S_e: strength factor for edge regions;
- S_f: strength factor for flat regions.

(If e.g. $S_f = 0$ and $S_e = 0$: pure denoising attack.)

2.4 Results of stochastic watermark removal

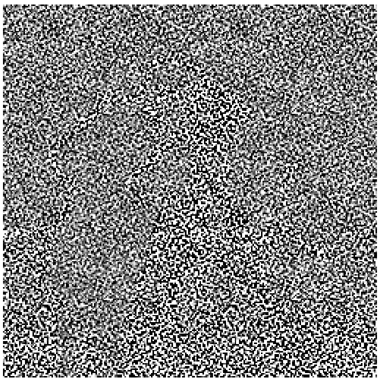
Software A, image 1:

original x

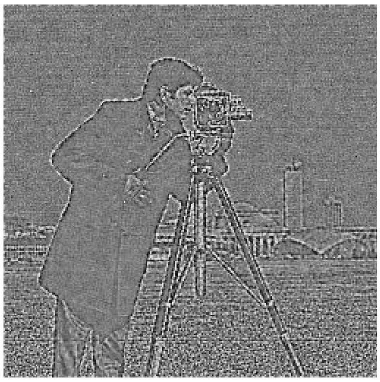
stego-image y
PSNR 34.7dB
wPSNR 35.7dB

$y'(S_e=2, S_f=1.5)$
PSNR 34.5dB
wPSNR 37.2dB

y - x



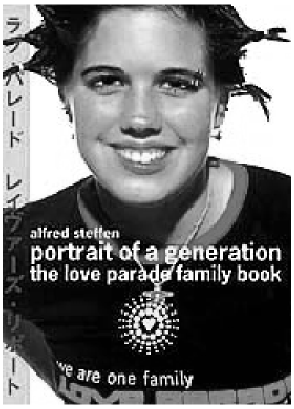
y’ - x

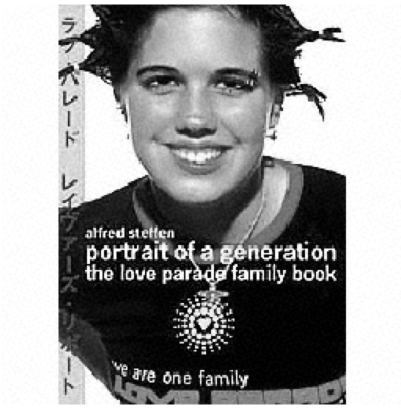


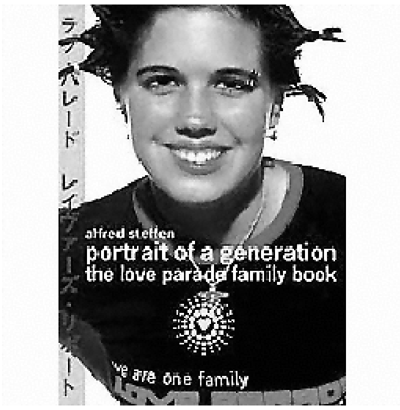
Message: *no watermark detected*.

Software A, image 2:

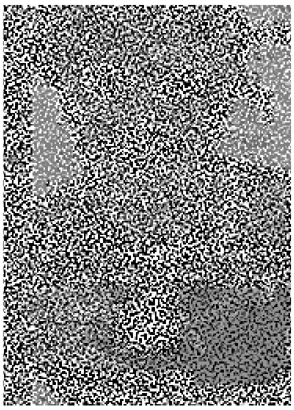
original x	stego-image y PSNR 35.8dB wPSNR 37.4dB	$y'(S_e=2, S_f=1.5)$ PSNR 35.3dB wPSNR 38.5dB







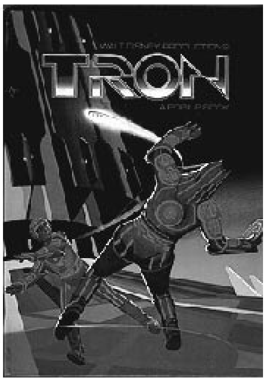
y - x	y' - x

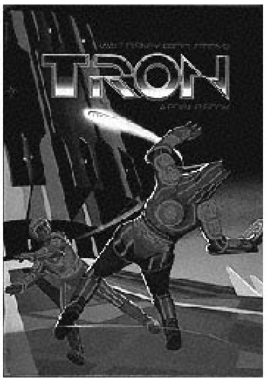


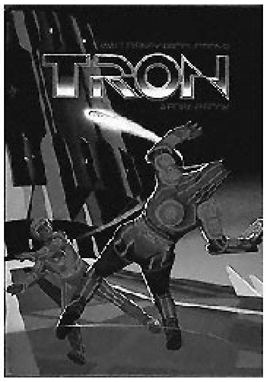

Message: *no watermark detected*.

Software A, image 3 (synthetic image):

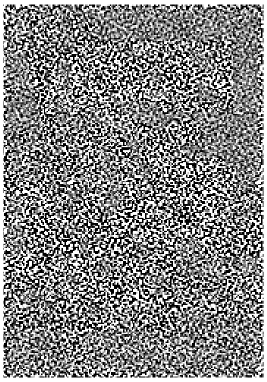
original x	stego-image y PSNR 35.4dB wPSNR 36.6dB	y'(S_e=2,S_f=1.5) PSNR 35.1dB wPSNR 38.1dB



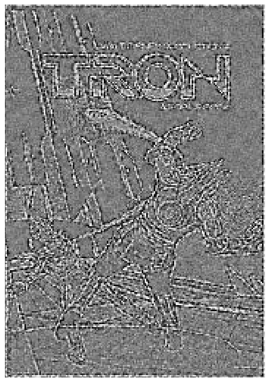




y - x

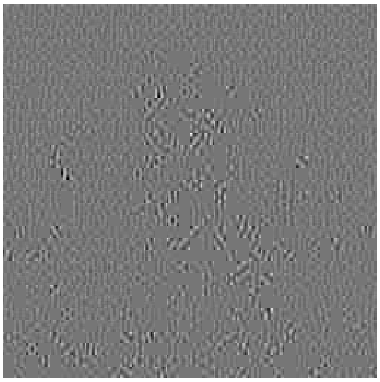
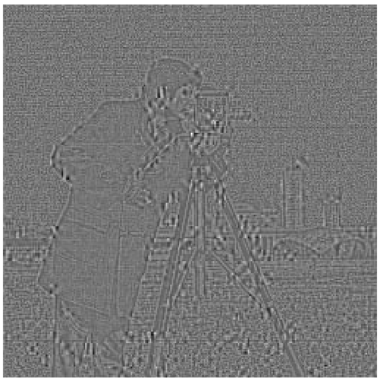


y' - x



Message: *no watermark detected*.

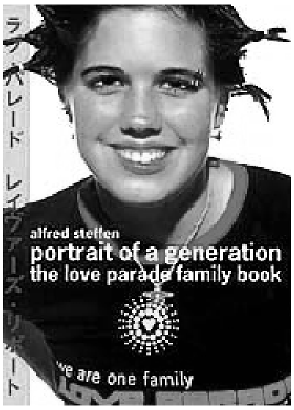
Software B, image 1:

original x	stego-image y PSNR 41.5dB wPSNR 42.5dB	$y'(S_e=2, S_f=1.5)$ PSNR 39.1dB wPSNR 40.6dB
		
	y - x	y' - x
		

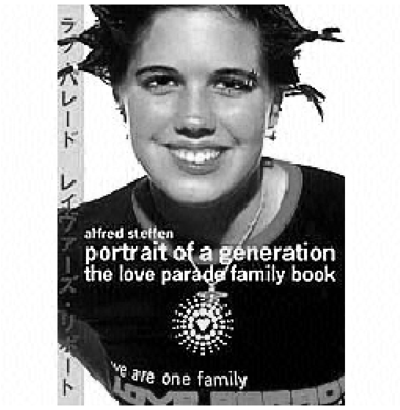
Message: *no watermark detected*.

Software B, image 2:

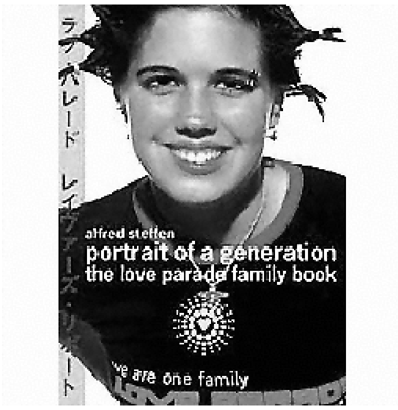
original x



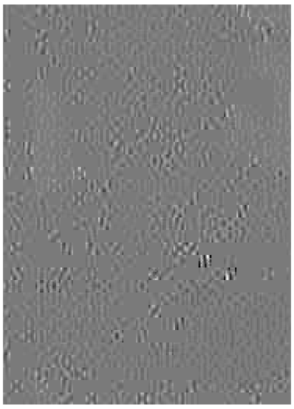
stego-image y
PSNR 41.5dB
wPSNR 42.9dB



$y'(S_e=2, S_f=1.5)$
PSNR 38.7dB
wPSNR 41.3dB



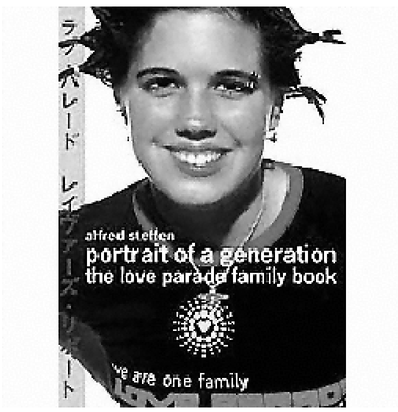
y - x



y' - x

Other parameters:

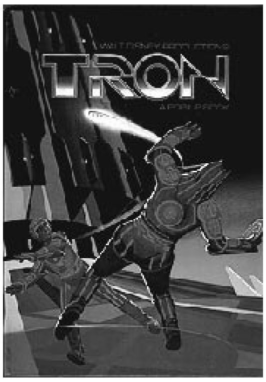
$y'(S_e=1, S_f=1.2)$
PSNR 40.5dB
wPSNR 42.6dB



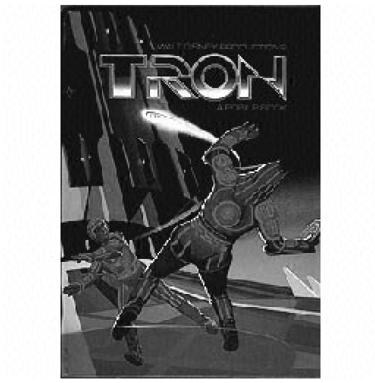
Message: *no watermark detected*.

Software B, image 3 (synthetic image):

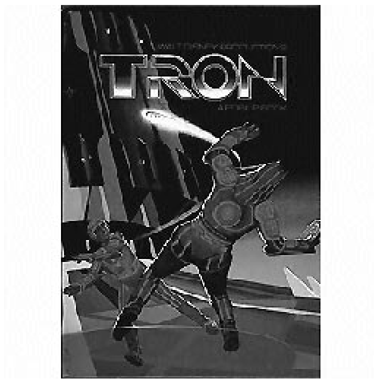
original x



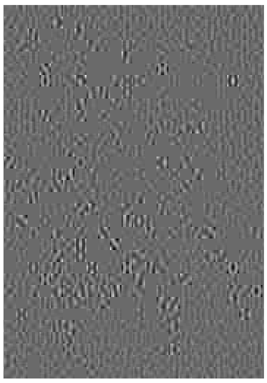
stego-image y
PSNR 41.2dB
wPSNR 43.1dB



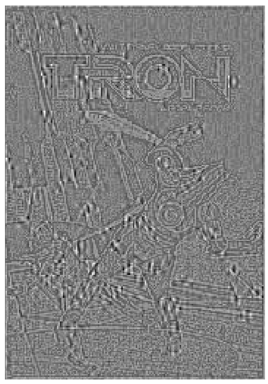
y’(S_e=2,S_f=1.5)
PSNR 38.9dB
wPSNR 41.4dB



y - x



y’ - x



Message: *no watermark detected*.

3. Synchronization attacks

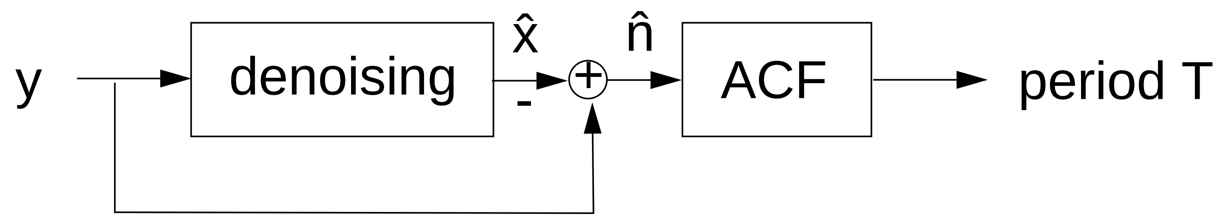
3.1 Introduction

Goal: desynchronize spread-spectrum sequence.

Means of attack:
- (geometric distortions;)
- template search and removal:
  - known pattern (cross, sine wave);
  - peaks;
- ACF analysis.

3.2 ACF analysis

Use knowledge from ACF to determine period T:



Knowing T:
- better estimate of watermark → easier removal;
- modify estimated watermark $\hat{n}$ to cancel ACF.

3.3 Template removal

Goal: remove synchronizing template.

Principle: identify template peaks in FT domain.

Algorithm:

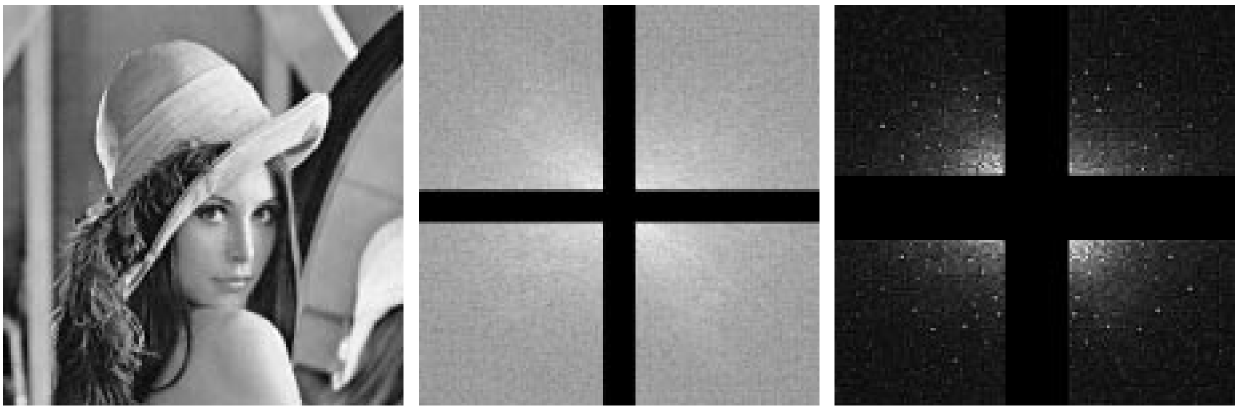
- cut the stego-image y into adjacent blocks;
- average the Fourier transforms of the blocks;
- estimate stable peaks as template peaks;
- Fourier transform the entire image;
- remove template peaks at the identified locations.

Example:

stego-image y

FT(y) no visible peaks

FT(y) after blocking and averaging



4. Conclusions

State-of-the-art: possible to hide/remove any watermark while preserving image quality.

Final remarks:

- very useful to study watermark attacks;
- watermarking methods should make use as much as possible of image and watermark statistics;
- assume attackers know your method
  → Kerkhoff’s principle.

Final final remark: the bad guys are always one step ahead ...

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DCT digital copyright technologies

EPFL ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE