A New Blind Color Image Watermarking Based On A Psychovisual Model And Quantization Approaches

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Introduction

Definition

- Embed a hidden message into a host image.
- Robustness of the watermark to various image processings such as JPEG compression, amplitude scale change, noise, filters, ...

Contributions

- Algorithm for color images.
- Improvement of watermark invisibility using a psychovisual model of the Human Visual System (HVS).
- Improvement of watermark robustness compared to performances in grayscale.

Literature

Color watermarking algorithms

- Blue component (Kutter et al. 1997)
  $\rightarrow$ Low sensitivity of the HVS in this channel.
- Luminance and Saturation components (HSV) (Yu et al. 2001)
  $\rightarrow$ Robustness with high energy components with reduced watermark invisibility.
- 3D vector approach : eigen image concept and PCA decomposition (Abadpour et al. 2008)
  $\rightarrow$ Vector quantization on color pixel values.
- Color histogram approach (Chareyron et al. 2006)
  $\rightarrow$ Uses the HVS low sensibility to perceive small color differences.

Grayscale to color quantization

Embedding

- For all color pixel P,

$$P' = P + k.u_P \qquad (1)$$

$$k = (Q(K) - K)/\|u_P\|^2 \qquad (2)$$

with Q a quantization function (such as Lattice QIM quantizer), $K =< P, u >$ and u a direction vector.

Direction vector choices

1. Constant Approach (CA) : u_P is constant.
2. Adaptive Approach (AA) : u_P is psychovisually adapted to color P to minimize visual quantization noise.

Direction vector strategies

Detection

- From the modified value of P' noted P'', estimate $Q(K)$. We have :

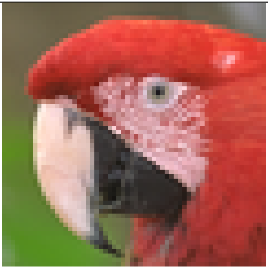
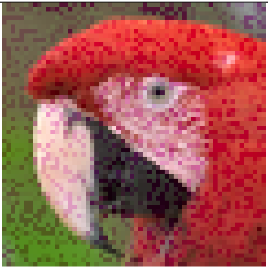
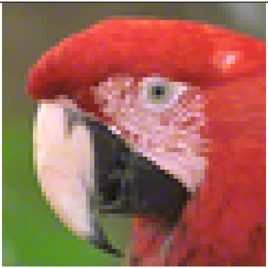
$$Q(K) =< P', u_P >\simeq< P'', u_{P''} > \quad (3)$$

Conditions for detection

1. If P' and P'' are different, we need u_P and $u_{P''}$ close enough to ensure detection.

Color problem

→ Same numerical distortion for both approaches.

Host image	CA (random vector)	AA
		

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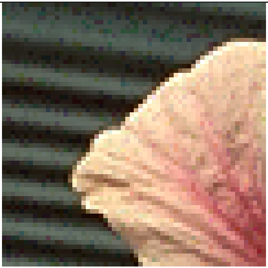
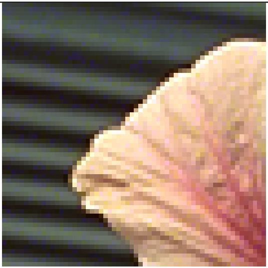
		

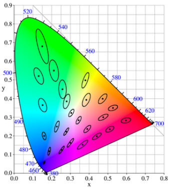
Color differences perception

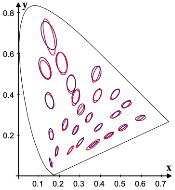
JND concept

- Extension of MacAdam Ellipses to 3D.
  $\rightarrow$ Construction of perception ellipsoids with constant psychovisual distortions in RGB.

Model calibration

- Ellipsoids converted in the luminance plane xyY.
- Constants calibrated to fit MacAdam ellipses.





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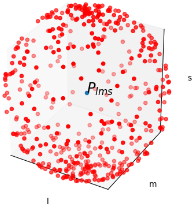
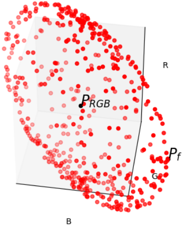
Biological model

- Perception is a non-linear phenomenon.
  → Photoreceptor model for cones *L*, *M* and *S* in the human retina.

$$x = \frac{\alpha X}{X + X_0} \tag{4}$$

Perception volumes

→ Distortions between the center P_{RGB} and points on the surface.

Distortion	Sphere in *lms*	Ellipsoid in *RGB*
		
Numerical	constant	**not constant***
Psychovisual	constant	constant

Perception volumes

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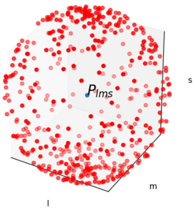
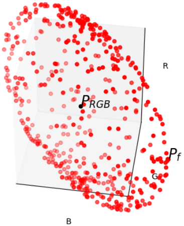
<table>
<tr><th>Distortion</th><th>Sphere in lms</th><th>Ellipsoid in RGB</th></tr>
<tr><td></td><td>
</td><td>
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* More numerical distortions by choosing the furthest points from P_{RGB} for the same psychovisual distortion cost.

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	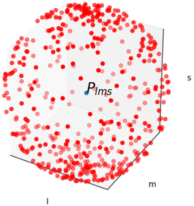	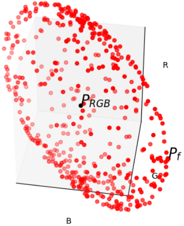
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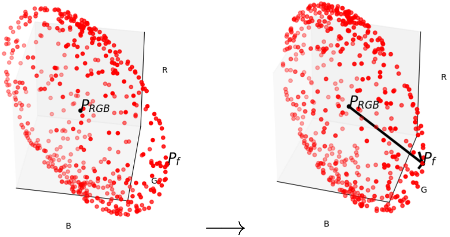
* More numerical distortions by choosing the furthest points from P_{RGB} for the same psychovisual distortion cost. $\Longrightarrow$ More robustness !

Direction vector extraction



Optimal direction for a better psychovisual invisibility

- Ellipsoid center P_{RGB} and furthest point from P_{RGB} noted P_f.

$$u_{P_{RGB}} = \overrightarrow{P_{RGB}P_f} \qquad (5)$$

$\rightarrow$ Psychovisual distortion is constant.
$\rightarrow$ Numerical distortion is maximized.

Embedding

1. For every colors P, compute u_{P_i}.
2. Compute $S_i =< P_i, u_{P_i} >$ for $1 \leq i \leq N_P$, N_P the number of quantized colors.
3. QIM embedding with $Q_m : S_i' = Q_m(S_i, \Delta)$ and $m = 0, 1$.
4. Compute the modified colors : $P_i' = P_i + (S_i' - S_i)u_{P_i} / \|u_{P_i}\|^2$.

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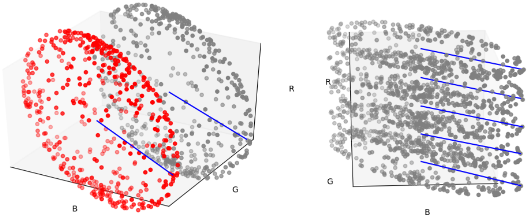
Detection

1. For every modified colors P'', compute $u_{P_i''}$.
2. Compute the scalars back : $S_i'' =< P_i'', u_{P_i''} >$.
3. Apply QIM decoder on the modified scalars S_i''.

Detection and robustness



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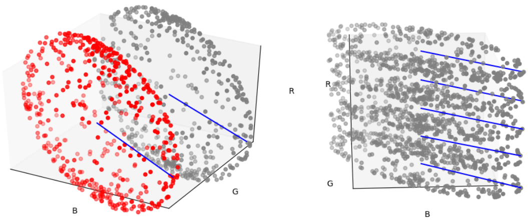
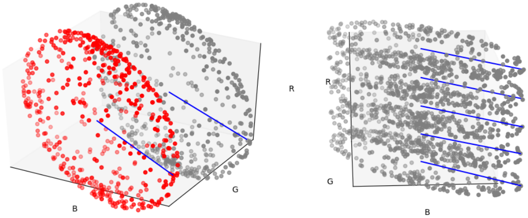


Direction stability

→ Direction vectors are stable from one color to another.

Detection and robustness



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In practice

→ From grayscale to color methods : we can have robustness improvements.

Validation protocol

Implementation details

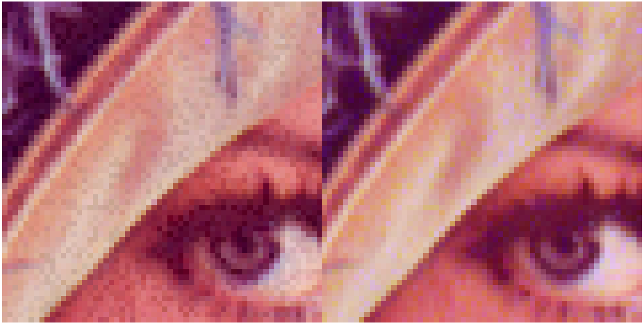
- Lattice QIM (LQIM) : vector quantization on lattice cosets Λ_0 and Λ_1.
- Soft Decision Detection QIM (SDQIM).
- Grayscale and color methods with the same numerical distortion respectively.
- Image processings : JPEG compression, gaussian noise.

Color adaptations

- Grayscale approach (GA)
  $\rightarrow$ Constant approach with $u = (1, 1, 1)$.
- Adaptive approach (AA)
  $\rightarrow$ Each color P has an adapted direction u_P.

Invisibility experiments

→ Visual validation : pairs of images (GA/AA)



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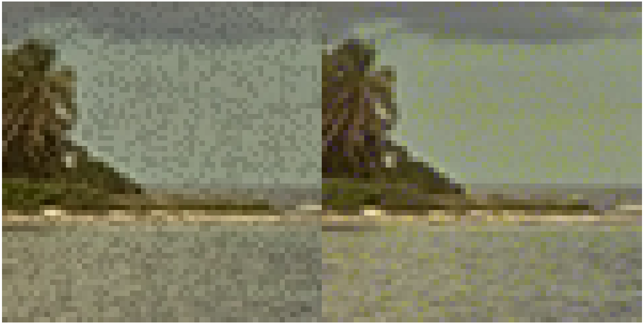

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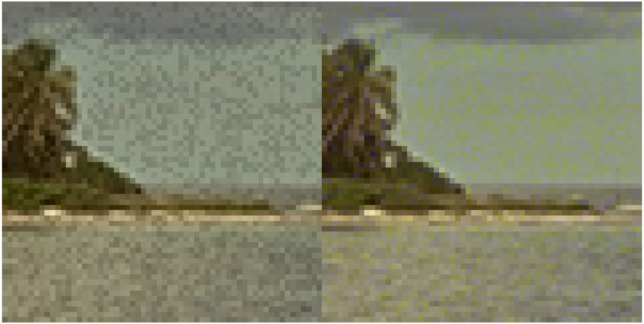
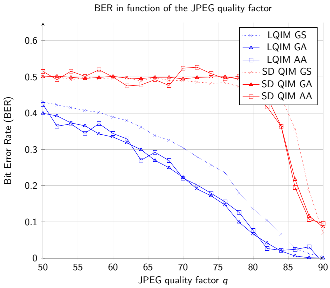
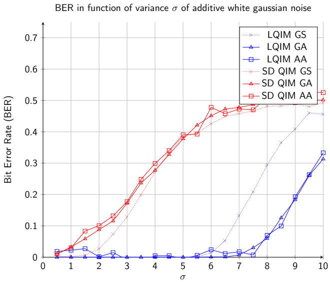


→ Tests subjects validation : which image is less noisy ?

Approaches	GA	AA
Votes	$4\% \pm 3\%$	$96\% \pm 3\%$

Robustness experiments





Remarks

1. From GS to GA/AA : improvement for LQIM and stability for SDQIM.

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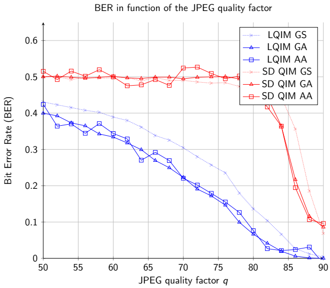

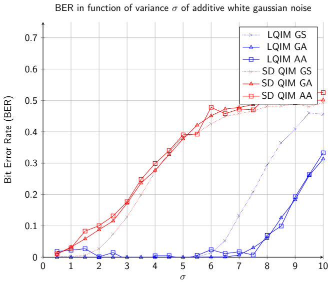

Remarks

1. From GS to GA/AA : improvement for LQIM and stability for SDQIM.
2. Similar performances of (GA)/(AA) but better visual quality for (AA).

Conclusion and perpectives

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- Adaptability of any grayscale watermarking method to color.
- Watermark invisibility and robustness improvements.

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Perspectives

- Make a visual quality evaluation with more test subjects.
- Study of this approach in transformed spaces such as DCT or DWT domains.
- Reduce errors by using error correcting codes such as BCH or RS codes.

Thank you for your attention ! Any question ?