A NEW BLIND COLOR IMAGE WATERMARKING BASED ON A PSYCHOVISUAL MODEL AND QUANTIZATION APPROACHES

Pascal Lefèvre[⋆] *Philippe Carré*[⋆] *Philippe Gaborit*[†]

[⋆]XLIM laboratory, UMR CNRS 7252, University of Poitiers, BP 30179, 86962 Futuroscope Chasseneuil
[†]University of Limoges, 123, avenue Albert Thomas - 87060 LIMOGES CEDEX, France
pascal.lefevre@univ-poitiers.fr, philippe.carre@univ-poitiers.fr, philippe.gaborit@xlim.fr

ABSTRACT

Over the last few years, considering 3D vectors as one color information instead of three independent vector components has significantly improved the color watermarking field. There have been some research about perceptual approaches but there are few about the perception of color differences of the human vision system (HVS) for watermarking applications.

This paper propose a new color watermarking algorithm able to minimize the perception of color differences. It understands color information as the HVS does. It can easily be adapted to many watermarking schemes such as quantization based schemes [1] or spread spectrum insertion techniques.

This algorithm is based on a psychovisual model of the human eye studied by D. Alleysson [2]. The results showed good improvements in terms of watermark invisibility and robustness to image processings: we compared quantization methods working in grayscale and its color adaptation to show model stability or improvement.

***Index Terms*—** watermarking, color, vector approach, psychovisual model, human visual system

1. INTRODUCTION

The literature contains numerous color watermarking algorithms. The first solutions (for example [3, 4]) proposed to select the blue channel in order to minimize perceptual changes in the watermarked image. Then, other methods consisted in modifying the intensity component [5] or the saturation component [6]. These methods considered the color information as three independent vector components which lead to robustness problems.

After that, some methods manipulating the color vector as one information appeared. Abadpour et al. [7] used a PCA decomposition. They developped a three dimensional vector approach based on eigen images but doesn't take into account the HVS. The watermarking technique developped by Chareyron and Trémeau [8] was specifically designed for color images. The watermark is embedded into the color domain and takes advantage of the low sensitivity of the human visual system (HVS) to perceive small color differences. This work is a first step towards the base concept we are about to introduce. Moreover, recent works have been done on color watermarking using transform domains and SVD decomposition but don't consider color as the human visual system does such as [9, 10].

We thank David Alleysson for sharing some discussions about the psychovisual model and all the people who helped us make this a better article. Of course, we also thank Délégation Générale de l'Armement for funding.

So far, no-one has fully investigated the perception of color differences. In our work, we propose a 3D quantization algorithm (section 2) minimizing the perception of color differences of the HVS. It is based on a psycho-visual mathematical model of the HVS (section 3) proposed by D. Alleysson [2].

We validate our new method with experiments on two well known QIM methods (SD-QIM and Lattice QIM defined in section 4) on watermark invisibility and robustness (section 5) to some image processings such as JPEG compression and additive white gaussian noise.

2. COLOR QUANTIZATION

There are various color representations such as RGB colorspace which is one of the most used representation. From [11], the perception of color differences is a non-linear phenomenon.

Inspired from this fact and the quantization techniques in grayscale, we define a vector quantizer to embed scalar modifications (for example the famous QIM method [12]) where we can clearly see that if we don't choose vector u correctly, the HVS may perceive a stronger color distortion. We modify a color P into P' such that:

$$P' = P + (Q(< P, u >) - < P, u >).u \tag{1}$$

with Q a QIM quantizer and u a direction vector in a colorspace. Now, we can illustrate the non-linear behavior of colors perception. Equation 1 modifies color P according to the quantization of K along the direction axis u.

To show how the choice of u important, consider the numerical example:

- $P = (100, 100, 100)$ a color (a grayscale),
- $u_P = (0, 0.994, 0.152)$ an optimal direction,
- $u = (1.003, 0.001, 0.002)$ a random direction.

We simulate an increasing quantization noise with $k = 1, ..., 30$. For $k = 30$, $P_2 = P + k.u_P$ becomes red while $P_1 = P + k.u$ is gray very close to a green. When comparing both colors with P, P_1 minimizes the color distortion for the HVS.

Direction vector u must be chosen carefully if a watermark requires maximum invisibility. As seen in the previous example, there exists an optimal choice of direction vector u_P to minimize color differences perception. This concept already exists for grayscale watermarking. In [13], Watson's model is used with a quantization scheme, to modulate the quantization step in order to minimize the perception of grayscale differences.

It is important to discuss the difficulty to retrieve vector u after image processing. If u is not constant, before the decoding step, we must guess the correct scalar value $< P', u >$, i.e., we need to guess the direction vector. In the next section, we show how to choose the optimal direction vector u_P for watermarking, for any color P.

3. PSYCHOVISUAL APPROACH TO THE HVS

3.1. Photoreceptor model

In the human retina, there are three types of photoreceptors to capture the color information: Large, Medium and Small cones. By measuring the electrical responses to different flash light intensities of every cones, the non-linearity or color vision was demonstrated (chapter 4 of [14]).

More precisely, these experiments showed that color perception depends on the adaptation state of the HVS which fits particularly well the Naka-Rushton law (Kinetics of photoreceptors). It is given by the formula:

$$x = f(X, X_0) = \frac{X}{(X + X_0)} \tag{2}$$

with x the transduction level, X the excitation level of the cone produced by the light and X_0 the adaptation state. X_0 modifies itself in function of the average excitation level of the photoreceptor.

Based on the work of D. Alleysson [2], we model a surface volume $\mathcal{E}$ of center P_{RGB} in RGB colorspace where any element of $\mathcal{E}$ has the same level of color difference perception with its center.

3.2. 3D model

Each cone is parametrized such that:

$$l = \alpha_L f(L, L_0) \text{ with } \alpha_L = 1665, L_0 = 66, \tag{3a}$$

$$m = \alpha_M f(M, M_0) \text{ with } \alpha_M = 1665, M_0 = 33, \tag{3b}$$

$$s = \alpha_S f(S, S_0) \text{ with } \alpha_S = 226, S_0 = 0.16. \tag{3c}$$

Factors α_L, α_M and α_S are gains, and L_0, M_0 and S_0 are adaptation states of L, M and S cones respectively. These constants are chosen to obtain the best fitting with Mac Adam ellipses in xyY colorspace (computed in chapter 4 of [14]) so that our model can simulate the HVS behavior. This model extends Mac Adam's work [15]: instead of having ellipses (constant luminance place), we have a three dimensional representation of color just noticeable difference (JND).

In figure 1, we show the transformation of a sphere (of center $P_{lms} = (23, 48, 195)$ in the lms space to the RGB space. On the right side of figure 1, we can see the transformation of the sphere into an ellipsoid $\mathcal{E}$ of center $P_{RGB} = (200, 255, 255)$.

3.3. Direction vector extraction

Pseudo-ellipsoid $\mathcal{E}$ of center P_{RGB} represents the set of points that produce the same color difference perception from P_{RGB}. Choosing the furthest point P' from P_{RGB} minimizes the perception of color differences for the largest distance: our extracted direction vector is $u_P = \overrightarrow{P' P_{RGB}}$. For every RGB color P_{RGB}, we can compute a pseudo-ellipsoid and extract the optimal direction.

In the context of watermarking, choosing a different direction vector for quantization (with the same robustness parameters) produces a more visible distortion.

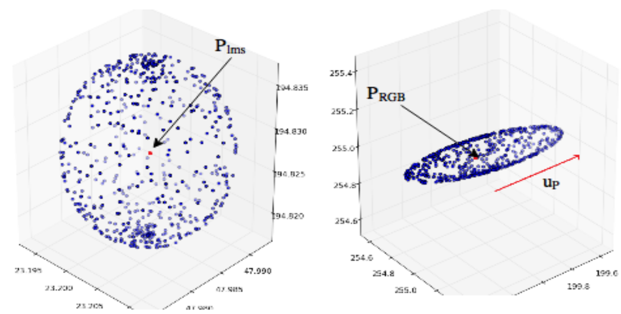

Fig. 1. On the left: sphere in lms space (the transduction space) of center P_{lms} and on the right: volume in RGB colorspace (set of points) of center P_{RGB} computed from the left sphere. This figure illustrates the non-linear phenomenon of color perception in the RGB colorspace: in the lms space, each point of the sphere has the same difference color perception with the P_{lms}. When those lms points are converted in RGB, we obtain a volume similar to an ellipsoid.

4. COLOR ADAPTATION OF QIM METHODS

Two of the most famous QIM methods were arbitrarily chosen for color adaptation. We briefly define them in this section. Constant L is the redundancy parameter (or lattice dimension for L-QIM) and Δ the quantization step.

4.1. QIM methods

4.1.1. Lattice QIM (L-QIM)

Vector quantization was introduced by B. Chen and Gregory W. Wornell [12]. For the embedding, we have two cosets of the lattice $(\Delta\mathbb{Z}^L)$ cosets of dimension L and a quantizer Q_m:

$$\Lambda_0 = -\frac{\Delta}{4} + \Delta\mathbb{Z}^L, \Lambda_1 = \frac{\Delta}{4} + \Delta\mathbb{Z}^L \tag{4a}$$

$$y = Q_m(x, \Delta) = \lfloor x/\Delta \rfloor \Delta + (-1)^{m+1}\Delta/4, m = 0, 1 \tag{4b}$$

with x a host sample and y the result of its quantization.

For detection, we compute which coset is closer to the received vector z:

$$\hat{m} = \arg\min_{m \in \{0,1\}} dist(z, \Lambda_m), \tag{5a}$$

$$dist(z, \Lambda) = \min_{y \in \Lambda} \|z - y\|_2 \tag{5b}$$

with z a corrupted version of a quantized vector y.

4.1.2. Soft Decoder QIM (SD-QIM)

This algorithm is an extension of the scalar QIM method. The key idea is to repeat message bit to enhance robustness. A host vector sample $s \in \mathbb{R}^L$ is quantized with bit b with Q_b. The decoder is:

$$\hat{m} = \arg\min_{b \in \{0,1\}} \sum_{i=1}^{L} |z_i - Q_b(z_i, \Delta)| \tag{6}$$

with z a corrupted version of a quantized vector y. Now, we have defined all the tools required to explain our color watermarking methods.

4.2. Color algorithm

We show how to embed a color watermark with QIM methods. The first step consists in computing u_{P_i} and $S_i = < P_i, u_{P_i} >$ for $1 \leq i \leq N_P$, N_P the number of quantized colors. Secondly, use QIM quantization: $S'_i = Q_m(S_i, \Delta)$ and $m = 0, 1$. Thirdly, modify colors P_i such that $P'_i = P_i + (S'_i - S_i)u_{P_i}$.

At detection, apply the first step on the corrupted version of color pixels P''_i and use the adequate QIM decoder on the corrupted scalars $S''_i = < P''_i, u_{P''_i} >$.

Fig. 2. Comparisons with a cropped version of Lenna original picture 60×60 with an embedding rate of $1/2$. The first line of small image have been watermarked with the constant approach (GA) and the second line with the adaptive approach (AA). For each column, both images were watermarked with the same DWR decreasing from the left to the right: $-6.12, -6.25, -6.34$ respectively (the first column being the original crop). Embedding rate and random embedding positions were fixed for one column.

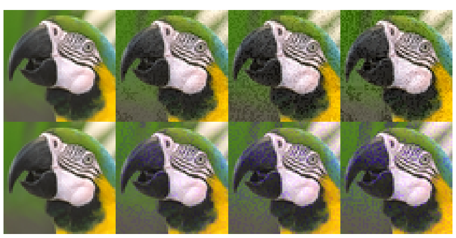

Fig. 3. Cropped version of Kodak image 'kodim23' with same experimental conditions as in figure 2. For each column, both images were watermarked with the same DWR decreasing from the left to the right: $-2.04, -2.12, -2.17$ respectively (the first column being the original image crop). We can see severe distortions of the background scene on the first line as the level of distortion increases. On the second line, this is not the case but instead, a blue spot appeared on the parrot beak.

5. EXPERIMENTS AND RESULTS

To demonstrate the effectiveness of our method, we focus on watermark invisibility and robustness improvements. For both experiments, we used the Kodak image database and watermarked in the spatial domain. For robustness experiments, more BER measures were made with the Corel image database (1000 images randomly chosen among the 10000 images available) and showed similar results.

Choices	Constant approach	adaptive approach
Average votes	$4\% \pm 3\%$	$96\% \pm 3\%$

Fig. 4. Psychovisual experiment on test subjects who were asked to vote for the least damaged image after quantization by looking at a host image, its corresponding watermarked images with constant and adaptive approaches at equal DWR = 20dB, ER = $1/2$ and same random positions. This table shows the percentage of images less damaged with each approach.

5.1. Watermark invisibility

In our model, a simple approach is to use a constant direction vector $u = (1, 1, 1)$ and a second one adapts its direction in function of the color. Direction u represents the lumimance axis: it is the most stable direction for color preservation. Choosing another random direction will produce wrong colors.

The adaptive approach provides a better watermark invisibility for the same level of distortion (Document-to-Watermark-Ratio (DWR)) than the constant approach for the HVS. In figure 2, the first line of watermarked images with the constant approach contains more quantization noise than the ones in the second line (adaptive approach) at equal DWR and Embedding Rate (ER). Figure 3 is an additional example that confirms invisibility is better with the adaptive approach. Both figures were watermarked with Lattice QIM method with $\Delta = 30, 40, 50$ respectively from the second line to the fourth columns.

To validate the psychovisual improvements, we made a psychovisual experiment presented in table 4 with the same parameters in figure 2. For every test subject, we can see that only 4% of images were claimed to be less damaged with the constant approach. For almost all images, we can conclude that watermarking with the constant approach leads to poorer watermark invisibility compared to the adaptive approach.

5.2. Robustness

For each attack and each method, we considered the Bit error rates (BER) for grayscale images (denoted by GS) and for color images with grayscale axis (GA) and adaptive axis (AA). To correctly appreciate BERs, we ran our performance tests over 100 repetitions for one set of parameters. Every BER averages has a standard deviation $\sigma \leq 0.01$.

Each RGB image was watermarked with an embedding rate of $1/32$ (the number of bits message n times the vector length L over the total number of color pixels). JPEG compression and additive white gaussian noise are two of the most common image processings and were arbitrarily chosen to compute our performance results.

In figures 5 and 6, GA and AA curves show lower BER than their respective GS curve. From this observation, we see that our color method improves the robustness for the same signal distortion (DWR = 35dB and 25 dB) of L-QIM method. However, we only have robustness stability SD-QIM method.

Using DWR of 35dB provides an invisible watermark but we only use 25dB to show the stability of our psychovisual model for SD-QIM method. Moreover, the results show that GA curves and its respective AA curves are almost the same. It experimentally shows that a distortion on a color pixel P produces a weaker distortion on its associated scalar $S = < P, u_P >$.

Finally, one can note that the same robustness performance can be obtained with the same numerical level of distortion for GA and

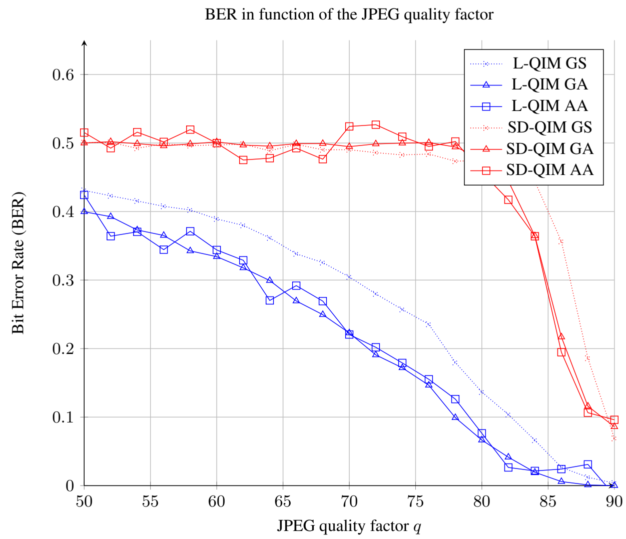

Fig. 5. Bit error rate in function of the JPEG compression quality factor q for Lattice QIM (DWR = $35dB$) and Soft Decoding QIM (DWR = $25dB$) and their corresponding color adaptations (GA) and (AA) with ER = $1/32$.

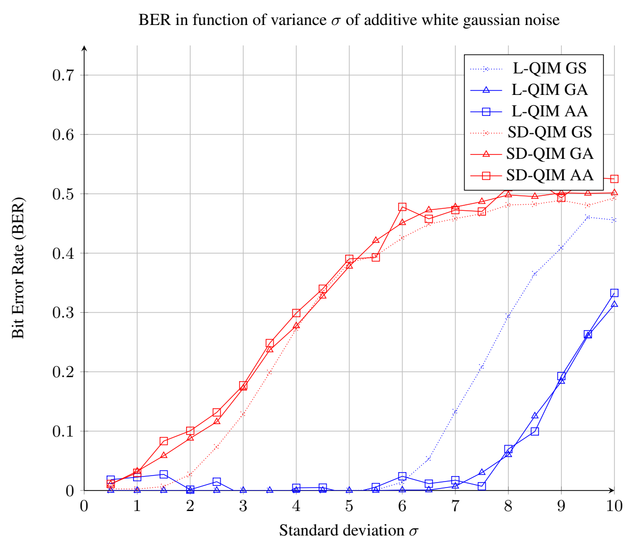

Fig. 6. Bit error rate in function of an additive white gaussian noise for Lattice QIM (DWR = $35dB$) and Soft Decoding QIM (DWR = $25dB$) and their corresponding color adaptations (GA) and (AA) with ER = $1/32$.

AA curves. In practice, the adaptive approach gives a more invisible watermark and improves the invisiblity/robustness tradeoff.

6. CONCLUSION

We proposed a color technique which can adapt some of the well known grayscale watermarking methods. Compared to the literature on color watermarking, we propose a method that 'understands' colors as the human eye. It is based on a psychovisual approach of the HVS with mathematical models. For any color pixel, we can compute an optimal direction vector to minimize the color differences perception.

The visual image quality was validated by a small amount observers. However, we plan to make a psychovisual experiment with more test subjects.

For color watermarking robustness, we obtained lower BERs compared to grayscale watermarking. With the adaptive approach, we improved the quality/robustness tradeoff by improving the watermark invisibility and in some cases, the robustness.

The perspectives for this model are to work in transformed spaces such as DWT or DCT to reduce the amount of errors and take into account more improvements proposed in [2].

7. REFERENCES

[1] P. Moulin and R. Koetter, "Data-hiding codes," *Proceedings of the IEEE*, vol. 93, no. 12, pp. 2083–2126, Dec 2005.

[2] David Alleysson and David Méary, "Neurogeometry of color vision," *J Physiol Paris*, vol. 106, no. 5-6, pp. 284–96, Mar. 2012.

[3] Martin Kutter, Frederic D. Jordan, and Frank Bossen, "Digital signature of color images using amplitude modulation," 1997, vol. 3022, pp. 518–526.

[4] Pao-Ta Yu, Hung-Hsu Tsai, and Jyh-Shyan Lin, "Digital watermarking based on neural networks for color images," *Signal Processing*, vol. 81, no. 3, pp. 663 – 671, 2001, Special section on Digital Signal Processing for Multimedia.

[5] G. Voyatzis and I. Pitas, "Digital image watermarking using mixing systems," *Computer & Graphics*, vol. 22, pp. 405–416, 1998.

[6] Hee-Soo Kim, Ho-Keun Lee, Ho-Young Lee, and Yeong-Ho Ha, "Digital watermarking based on color differences," 2001, vol. 4314, pp. 10–17.

[7] Arash Abadpour and Shohreh Kasaei, "Color pca eigenimages and their application to compression and watermarking," *Image and Vision Computing*, vol. 26, no. 7, pp. 878–890, 2008.

[8] Gaël Chareyron and Alain Trémeau, *Color Images Watermarking Based on Minimization of Color Differences*, pp. 82–89, Springer Berlin Heidelberg, Berlin, Heidelberg, 2006.

[9] Channapragada Rama Seshagiri Rao and Munaga V. N. K. Prasad, *Color Image Watermarking Techniques Based on Magic Square and Ridgelets*, pp. 59–74, Springer International Publishing, Cham, 2016.

[10] Jianzhong Li, Qun Lin, Chuying Yu, Xuechang Ren, and Ping Li, "A QDCT- and SVD-based color image watermarking scheme using an optimized encrypted binary computer-generated hologram," *Soft Computing*, pp. 1–19, 2016.

[11] Kasson S. Gibson, "Handbook of colorimetry," *Science*, vol. 85, no. 2214, pp. 545–546, 1937.

[12] Brian Chen and Gregory W. Wornell, "Quantization index modulation: A class of provably good methods for digital watermarking and information embedding," *IEEE TRANS. ON INFORMATION THEORY*, vol. 47, no. 4, pp. 1423–1443, 1999.

[13] Qiao Li and Ingemar J. Cox, "Using perceptual models to improve fidelity and provide resistance to valumetric scaling for quantization index modulation watermarking," *Information Forensics and Security, IEEE Transactions on*, vol. 2, no. 2, pp. 127–139, June 2007.

[14] David Alleysson, *Le traitement du signal chromatique dans la rétine: un modle de base pour la perception humaine des couleurs*, Ph.D. thesis, Université Joseph Fourier-Grenoble 1 Sciences et Géographie, March 1999.

[15] David L. MacAdam, "Visual sensitivities to color differences in daylight∗," *J. Opt. Soc. Am.*, vol. 32, no. 5, pp. 247–274, May 1942.