ABSTRACT
In this paper, we propose a method to embed the color information of an high dimension image in its corresponding grey-level image. The objective of this work is to allow a free and rapid access to the grey-level image and give color image access to secret key owners. This method is made of two steps which are the fast high-dimension color image decomposition (in a grey-level image and its associated color information) and the data-hiding. The two main contributions of this paper are the energy function proposed to model the decomposition of the color image and the fast optimization. The optimization of the proposed energy function leads to the achievement of an index image and a color palette. The good properties of that decomposition are an index image which is similar to the luminance of the color image and a color palette which is well suited for the data-hiding. The obtained results confirm the model quality and the real-time property.

1. INTRODUCTION
Nowadays, only few secure solutions are proposed, to protect digital painting data-base, in order to give both a free access to low-quality images and a secure access to the same images with a higher quality. Our proposed solution is built on a data-hiding method. The image may be freely obtained but its high quality visualization requires a secret key. More precisely, in our solution, a grey-level image is freely accessible but only secret key owners may rebuild the color image. Our aim is thus to protect the color information by embedding this information in the grey level image. Note that this work is envisaged to give a limited access to the private digital painting data-base of the Louvre Museum of Paris, France.

In order to obtain a grey-level image embedding its color information, we decompose a color image in an index image and a color palette. The color palette is then hidden in the index image. The index image should be similar to the luminance of the color image, the embedding process should be of weak magnitude and the color palette should be cleverly ordered. The originality of this paper is to propose a solution for this very constrained decomposition and this with real-time possibility. Thus, the main contribution is the energy function proposed to model the decomposition of the color image and the fast optimization of this model.

Many work propose solutions to hide information by using the decomposition of a color image in an index image and a color palette. The data-hiding may occur in the index image [1] or in the color palette [2, 3]. Nevertheless, none of those techniques tries to protect the color information by hiding the color palette in the index image. Only the previous work of [4] protect the color information by hiding the color palette in the index image. Authors of [4] sort the colors of the color palette in order to get an index image which closed the luminance of the original color image and in the same time they get a color palette whose consecutive colors are close. In this paper, the approach is completely different and relies on a function optimization of the global problem formulation.

Other works such that [5, 6, 7] based on wavelet decomposition and sub-band substitution propose solutions to embed the color information in a grey-level image. Their areas are perceptual compression and image authentication for [5, 6] and image printing for [7]. Even if those techniques embed the color information, their approach and their purpose are clearly different from that exposed in that paper.

In section 2, we present the proposed energy model. Section 3 deals with the secured data-hiding. In section 4, results are presented and analyzed.

2. ENERGY MODEL
In the section below, one propose a mathematical model for the decomposition of a color image in an index image plus an associated color palette. In the section 2.2, a second model close to the first one is introduced in order to find a fast and cheap memory solution for this decomposition. Finally, in section 2.3, we present a Fast Decomposition Algorithm which is approaching the minimum of the first model.

2.1. First model
Our goal is to find an index image and a color palette with the following three constraints:
• the index image should be close from the luminance of the original color image,
• the color quantized image should be close from the color image,
• and the color palette should own consecutive couples of close color.

Those three constraints come mathematically to found \( K \) colors \( C(k) \) (\( C \) is the color palette) and for each pixel \( i \) the index value \( \text{Index}(i) \). Thus, we are looking to minimize the above energy model in order to obtain \( \forall i \in [1, N] \), \( \text{Index}(i) \) and \( \forall k \in [1, K] \), \( C(k) \):

\[
E_1 = \sum_{i=1}^{N} (C(\text{Index}(i)) - I(i))^2 \\
+ \lambda_1 \sum_{i=1}^{N} (\text{Index}(i) - Y(i))^2 \\
+ \lambda_2 \sum_{k|k\in[1..K\text{ and } k \text{ is odd}} (C(k) - C(k+1))^2,
\]

with \( I \) the color image, \( Y \) the luminance image, \( \lambda_1 \) and \( \lambda_2 \) two scalar values.

The first term is expressing the constraint of color quantization. Its role is to exhibit the best representative \( K \) colors, i.e find \( C \), knowing the color image \( I \). The second term stand for getting the index image the nearest to the luminance image \( Y \). The last term constrain couples of consecutive color from the palette to be close.

The minimization of Equation 1 such that:

\[
\{P_{i,k}, C(k)\} = \arg \min_{\{P_{i,k}, C(k)\}} E_1,
\]

is not feasible by using derivative approach. Indeed, the function \( E_1 \) of Equation 1 is not derivable since the \( C \) function (\( C : [1..K] \rightarrow [0..255]^3 \)) is discrete. Instead of using meta-heuristic approaches (such that evolutionist algorithms) in order to solve the Equation 2, one prefer a less CPU and memory costly solution.

### 2.2. Second model

In order to solve rapidly the Equation 2, one propose to minimize another equation, whose solution is close, with a pixel sub-sampling of the color image. The new equation, minimized on the pixel sub-sampling, (in order to obtain \( \forall i, \forall k \), \( P_{i,k} \) and \( C(k) \)) is:

\[
E_2 = \sum_{i=1}^{N} \sum_{k=1}^{K} P_{i,k}^m (C(k) - I(i))^2 \\
+ \lambda_1 \sum_{i=1}^{N} \sum_{k=1}^{K} P_{i,k}^m (Y(i) - k)^2 \\
+ \lambda_2 \sum_{k|k\in[1..K\text{ and } k \text{ is odd}} (C(k) - C(k+1)^2,
\]

with \( P_{i,k} \) the ownership values giving the degree of belongingness of a pixel \( i \) to the \( k^{th} \) color and \( m \in [1, \infty[ \) the fuzzy coefficient tuning the equi-probability degree\(^2\). Note that \( P_{i,k} \) belongs to [0,1] and are named fuzzy membership values in fuzzy c-mean clustering approach [8]. Also note that the \( P_{i,k} \) give indirectly the index image such that: \( \text{Index}(i) = \arg_k \max_k P_{i,k} \).

The minimization of Equation 3 such that:

\[
\{P_{i,k}, C(k)\} = \arg \min_{\{P_{i,k}, C(k)\}} E_2,
\]

is performed iteratively, on a pixel sub-sampling, in a two steps loop as in conventional fuzzy c-mean algorithms. In the first step, colors \( C(k) \) are updated, given \( P_{i,k} \), by solving the linear system below:

\[
\forall k \text{ odd} : \sum_{i=1}^{N} P_{i,k}^m C(k) = \lambda_2 \times C(k) + \lambda_2 \times C(k+1) = \sum_{i=1}^{N} P_{i,k}^m I(i),
\]

\[
\forall k \text{ even} : \sum_{i=1}^{N} P_{i,k}^m C(k) = \lambda_2 \times C(k-1) + \lambda_2 \times \sum_{i=1}^{N} P_{i,k}^m C(k) = \sum_{i=1}^{N} P_{i,k}^m I(i).
\]

In the second step, \( P_{i,k} \) (with \( m=2 \)) are updated given the colors \( C(k) \) with:

\[
P_{i,k} = \left( \frac{\sum_{l=1}^{l=K} 2 \times ((C(k) - I(i))^2 + \lambda_1(Y(i) - I))^2}{2 \times ((C(k) - I(i))^2 + \lambda_1(Y(i) - k)^2} \right)^{-1}
\]

### 2.3. Fast Decomposition Algorithm

The Fast Decomposition Algorithm objective is to approach the minimum of Equation 2. As explain above, the optimization of Equation 1 on high dimension image is very CPU and memory costly if using meta-heuristic. Our solution is then to approach the minimum by choosing the best solution among a set of possible solutions. Those possible solutions are computed by using the minimization of the second model, explain in section 2.2 and with a limited amount of data i.e. a random selection of few pixels of the original high-dimension image.

The Fast Decomposition Algorithm iteratively repeat those three steps:

\(^{2}\)m is set to 2 for computational complexity reduction.
• Select randomly few pixels to create a small color image.
• Minimize Equation 3: A color palette $C$ is obtained and the index image $Index$ is deduced from Equation 1:

$$\forall i, Index(i) = \arg \min_k (C(k) - I(i))^2 + \lambda_1 (k - Y(i))^2$$

• Compute the fitting value $E1$ with another sub-sampling, knowing $C$ and $Index$, and keep this solution if it is the best one.

3. SPATIAL DATA HIDING METHOD

In this paper, we embed the color palette information in the LSB of the $N$ pixels index image. The objective is thus to embed a message $W$ made up of $l$ bits $b_j$ ($W = b_1b_2...b_l$). The embedding factor, in bit/pixel, is $E_f = l/N$. The index image is then divided in areas of size $\lceil 1/E_f \rceil$ pixels. Each area is used to hide only one bit $b_j$ of the message. This splitting procedure guarantees that the message is spread homogeneously over the whole image. In order to hide the color palette in the index image we need to embed $l = 3 \times 256 \times 8 = 6144$ bits (the number of colors is $K = 256$).

Consequently, the embedding factor $E_f$, only depends on the image size $N$. In our process, the PRNG (Pseudo-Random Number Generator) selects randomly, for each region, a pixel $Index(i)$. In order to get a marked pixel $Index_W(i)$, the LSB of this selected pixel $Index(i)$ is then modified according to the message bit $b_j$:

$$Index_W(i) = Index(i) - Index(i) \mod 2 + b_j$$

This way to embed the color palette ensure that each marked pixel is at worst modified by one grey-level and in the same time that the rebuilt color pixel would not be very far from the right color value. Indeed, the third term of Equation 1 ensures that consecutive couples of color are close.

4. RESULTS

We have applied our method on High-Dimension digital painting images. For all the experiments, $\lambda_1 = 1$, $\lambda_2 = 0.01 \times N/(K+1)$ and $m = 2$ (see Equation 1). The results obtained show that the approach is efficient whatever the image type. Below, the main steps of our approach are comment on a digital painting image ($8248 \times 11816$ pixels size) of the data-base of the Louvre Museum Paris. This painting shows a woman praying (Anonymous, Flandres, XVI century, Oil on oak).

After proceeding to the Fast Decomposition Algorithm on the woman praying image with $K = 256$ colors we obtain an index image illustrated in Figure 1.b and its color palette in Figure 2. This decomposition would have been impossible in a current desktop computer if proceeded on the full data. Indeed, the memory complexity necessary for the minimization of Equation 3 on the complete image is around 186 GB. With a sub-sampling of 9604 pixels (around 10000 times less pixels) the memory complexity is falling to only 19 MB which is little.

Let’s also note that even if the memory complexity would not have been problematic, the computation complexity would

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2This randomly sub-sampling image has no visual meaning.
3The formula is given for index values belonging to $[0,K-1]$.
4The memory complexity calculus is a low estimation; it takes into account $P_1,k, C(k), I(i), Y(i)$, and the linear system.
5A relatively cheap but modern desktop computer, for example, a Pentium 4, owns around 512 MB of RAM.
In this paper, we have proposed a method to embed securely into a grey level image its color information. This method is built on a fast decomposition of a color image in an index image and a color palette. The index image is playing the role of the luminance image and the color palette is hidden into this index image. The originality of this paper is to model the problem with an energy function whose solution is rapidly extracted even on high dimension images. Obtained results show a real improvement in comparison to [4] and are feasible on high dimension images. Our perspective work will treat of compression possibilities and other more robust data-hiding approaches.

5. CONCLUSION

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6. REFERENCES


