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Classification of painting techniques with color Run-Length Matrices

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Abstract

In human and computer vision, the analysis of color and texture is primordial for object recognition and image classification. The analysis of color textures mainly contributes to the automatic classification in industrial images, satellite images, bio-medical images, or patrimonial images. The aim of this paper is to propose a new color statistical measure for texture analysis, based on color Run-Length Matrices (cRLM), associated to Principal Component Analysis (ACP) for paintings classification. The effectiveness of our approach is assessed by results of perfect classification in a same group of the attributes space of all the paintings of an artist. These results suggest that color Run-Length Matrices are a suitable basis for color texture analysis in numerous applications based upon color textured regions classification.

Introduction

Image classification is one of the most important tasks in image analysis and computer vision since 1980s [1, 2, 3, 4], helpful for numerous applications, including pattern recognition and object tracking [5, 6, 7], skin detection and face tracking [8, 9], image retrieval [10, 11], defect detection and metrology [12, 13], biomedical and satellite or aerial imagery [14, 15, 16]. Color and texture provides important cues for all these applications but it's often difficult to combine these two main information. So, in this paper we present a new formulation for color Run-Length Matrices (cRLM) that we apply to the classification of different styles of painting. This study is part of a regional research project about digital patrimony. To begin, we realize a state of the art of texture and color analysis. Then we explain our methodology to compute cRLM and the associated attributes. Finally we describe the promising results obtained on a database of 6 paintings of 4 different artists before the conclusion.

Stat of the art for color texture classification

Texture and colour are important image properties for classification that have received significant interest from research community, with prior research generally focusing on examining separatly colour and texture features. A major problem is that textures in the real world are often not uniform, due to changes in orientation, scale or other visual appearance. In addition, the degree of computational complexity of many of the proposed texture measures is very high. So the main problem in color texture characterization and classification is to define the real characteristic parameters. In this part we will describe the main existing approaches for texture, color and color-texture analysis.

Texture Analysis

Texture hasn't a formal definition, it can be regarded as a function of the variation of pixel intensities which form repeated patterns [17, 18]. This fundamental image property has been the subject of significant research and is generally divided into four major categories: statistical, structural, model-based, and signal-based methods [19] as we can see on Table 1 from [20].

Table 1 : classification of texture analysis approaches

Category	Method
Statistical	1. Histogram properties 2. Co-occurence matrix 3. Local binary pattern 4. Other gray level statistics 5. Autocorrelation 6. Registration-based
Structural	1. Primitive measurement 2. Edge Features 3. Skeleton representation 4. Morphological operations
Filter Based	1. Spatial domain filtering 2. Frequency domain analysis 3. Joint spatial/spatial-frequency
Model Based	1. Fractal models 2. Random field model 3. Texem model

Statistical measures analyze the spatial distribution of the pixels using features extracted from first and second order histograms. Two of the most investigated statistical methods are the gray-level differences [21] and the co occurrence matrices [22], sometimes combined [23]. The co-occurrence matrices and their associated parameters are very popular [24, 25, 26, 27, 28, 29]. Another usual approach is the Local Binary Patterns (LBP) concept developed by Ojala et al [30]. that attempts to decompose the texture into small texture units and the texture features are defined by the distribution (histogram) of the LBP values calculated for each pixel in the region under analysis. These LBP distributions are powerful texture descriptors since they can be used to discriminate textures in the input image independently of their size. The dissimilarity between two or more textures can be determined by using a histogram intersection metric. An LBP texture unit is represented in a 3x3 neighborhood which generates 28 possible standard texture units. In this regard, the LBP texture unit is obtained by applying a simple threshold operation with respect to the central pixel of the 3x3 neighborhood. On another side, Galloway proposed the use of a run-length matrix for texture features extraction [31]. Various texture features can then be derived from this run-length matrix as we will explain in next part . The Model-based approaches include morphological image processing [32]. These methods are well adapted for macroscopic textures in which primitives and rules of geometrical arrangement are identifiable. Signal processing methods have been investigated more recently. With these techniques, the image is typically filtered with a bank of filters of differing scales and orientations in order to capture the frequency changes [33, 34, 35, 36, 37, 38]. Fisrt signal processing methods tried to analyse the image texture in the Fourier domain, but these approaches were clearly outperformed by techniques that analyse the texture using multi-channel narrow band Gabor filters. This approach was firstly introduced by Bovik et al [34] when they used quadrature Gabor filters to segment images defined by oriented textures. This approach was further advanced by Randen and Husoy [38] while noting that image filtering with a bank of Gabor filters or filters derived from a wavelet transform [39, 40] is computationally demanding. In their paper they propose the methodology to compute optimized filters for texture discrimination and examine the performance of these filters with respect to algorithmic complexity/feature separation on a number of test images. In the family of model-based methods, we can find the fractal description and the random field models. During the past years, several authors discussed to use multiresolution stochastic approaches to model textures [41]. Stochastic models consider textures as samples from a probability distribution on the image space. In this way, each pixel location is considered as a random variable. A parametric probabilistic model is then applied to this random field to obtain the joint or conditional probability distributions.

Color Analysis

Color is another important characteristic of digital images which has naturally received interest from the research community. This is motivated by advances in imaging and processing technologies and the proliferation of color cameras. Color has been used in the development of numerous classification algorithms that have been applied to many applications [42, 43, 44].

Color-Texture Analysis

Generally, authors proposed the use of a combination of color and texture features [45]. Texture features are computed in greyscale and combined with color histograms and moments [46, 47]. These combined features are then sent to a classifier for color-texture classification [48]. Other authors proposed the use of color quantization to reduce the number of colors and process the resulting image as greyscale for texture extraction [49, 50]. But the development of advanced unified color-texture descriptors may provide improved discrimination over viewing texture and color features independently. How best to combine these features in a color-texture mathematical descriptor is still an open issue, with strong links with the human perception modeling. To address this problem a number of researchers augmented the textural features with statistical chrominance features [51, 52]. The extra computational cost required by the calculation of color features is negligible when compared with the computational overhead associated. In the family of statistical approaches several authors have proposed color-cooccurrence matrices definitions [53, 54, 55]. Algorithms for color LBP have also been developed [56, 57, 58, 59]. Building on this, the paper by Pietikainen et al [60]. evaluates the performance of a joint color Local Binary Patterns (LBP) operator against the performance of the 3D histograms calculated in the Ohta color space. They conclude that the color information sampled by the proposed 3D histograms is more powerful then the texture information sampled by the joint LBP distribution. This approach has been further advanced by Liapis and Tziritas [61] where they developed a color-texture approach used for image retrieval using both statistical and signal approaches. In their implementation they extracted the texture features using the Discrete Wavelet Frames analysis while the color feature were extracted using 2D histograms calculated from chromaticity components of the images converted in the CIE Lab color space. Structural approaches using Morphological operators are also extended to color by numerous authors [62, 63, 64, 65]. Others researchers focused on color Model-based approaches using Markovian [66] or color fractal models [67].

Proposed approach based on RL Matrices

Original gray level approach

Introduced by Galloway [31], Run-Length Matrices have been defined to extract statistical features on the gray level distribution in image. A run is a set of collinear pixels with the same gray level in a given direction and the run length is the number of pixels in a run. The Run-Length Matrix $M_\Theta(n,l)$ contains the number of runs of length l for each gray level n for the direction Θ. Generally, four directions are used : horizontal, vertical and two diagonals ($\Theta = 0^o, 45^o, 90^o, 135^o$) are used. The maximum run length L_{max} is dependent of the direction and the images size or may be selected arbitrarily.

In [31, 68, 69], the Run-Length Matrices are used to characterize images textures with statistical features. They are defined by the following equations :

$$SLP = \sum_{n=1}^{N} \sum_{l=1}^{L_{max}} M_\Theta(n,l) \tag{1}$$

$$SRE = \frac{1}{SLP} \sum_{n=1}^{N} \sum_{l=1}^{L_{max}} \frac{M_\Theta(n,l)}{l^2} \tag{2}$$

$$LRE = \frac{1}{SLP} \sum_{n=1}^{N} \sum_{l=1}^{L_{max}} M_\Theta(n,l) \times l^2 \tag{3}$$

$$GLN = \frac{1}{SLP} \sum_{n=1}^{N} \left(\sum_{l=1}^{L_{max}} M_\Theta(n,l) \right)^2 \tag{4}$$

$$RLN = \frac{1}{SLP} \sum_{l=1}^{L_{max}} \left(\sum_{n=1}^{N} M_\Theta(n,l) \right)^2 \tag{5}$$

$$RP = \frac{SLP}{P} \tag{6}$$

$$LGRE = \frac{1}{SLP} \sum_{n=1}^{N} \sum_{l=1}^{L_{max}} \frac{M_\Theta(n,l)}{n^2} \tag{7}$$

$$HGRE = \frac{1}{SLP} \sum_{n=1}^{N} \sum_{l=1}^{L_{max}} M_\Theta(n,l) \times n^2 \tag{8}$$

where N is the number of gray levels in the image, L_{max} is the maximal run length and P is the number of pixels in the image.

The short run emphasis (SRE) is used to highlight the abundance of short run, inversely, the abundance of long run is appreciate by the long run emphasis (LRE). The feature gray level non-uniformity (GLN) is used to highlight the run distribution uniformity and the run length non-uniformity (RLN) increase when the number of same length run decrease. The run percentage (RP) measure the proportion of run in image or area. Finally the low gray level run emphasis (LGRE) and the high gray level run emphasis (HGRE) are two additional features to the SRE and LRE.

Our color adaptation

We propose an original method, cRLM, to adapt the run length matrix for color images. This method is based on color perception criteria: the Just Noticeable Difference (*JND*) and the distance metric ΔE [1] between two colors defined by the International Commission on Illumination (CIE). In a study by Mahy [70], a $JND = 2.3$ threshold is used to differentiate the two colors side by side as perceptually different. However, as proposed in [71], a *JND* between 3.5 and 5.0 provides a practical classification of a perceptibility color difference. Preliminary, the *RGB* images are converted into *CIELab* colorimetric space. The run $\mathbb{X}$ is determined with threshold (*JND*) on the distance ΔE between first pixel $pix(\mathbb{X}_0)$ and the *nth* collinear pixel $pix(nth)$. While equation 9 is valid, the collinear pixels are added to form a run and run length L is determined by the number of valid pixels.

$$pix(nth) \in \mathbb{X} \Rightarrow \Delta E(pix(nth), pix(\mathbb{X}_0)) < JND \quad (9)$$

Then, we choose as the representative color of the run, the median color C_{med} among the colors of the collinear pixels aggregated in the run. This value (equation 10) corresponds to the pixel color that minimizes the cumulative distance on $\mathbb{X}$, based on the distances ΔE, and represents the best perceptual color representative of the run.

$$C_{med} = pix(x) \in \mathbb{X} = \underbrace{arg\ min}_{pix(x)\in\mathbb{X}} \left(\sum_{l=0}^{L} \Delta E(pix(x), pix(l)) \right) \quad (10)$$

The median color C_{med} and run length L are included in the run length matrix $M_\Theta(n,l)$. There are two cases (see Algorithm 1): if the median color is already present in the matrix or very perceptually near of a present color (within the meaning of JND) then the value is added to the present matrix value for the corresponding color and the run length L. Otherwise, this median color is added in a new row of the matrix.

Finally, after repeating these operations on all image pixels and for all direction, we obtain four color Run-Length Matrices (cRLM) where each indexed color is perceptually distant of the other present colors in the matrix and corresponds to the median colors of the image runs. As with gray level Run-Length Matrices (RLM), the color image textures can be characterized by using statistical features in equations 1 to 8. Additionally, we recommend merging[2] the color Run-Length Matrices to obtain a general characterization of color textures.

[1] ΔE^*_{ab} CIE94 - this color difference is applied in the $L^*a^*b^*$ color space.
[2] process similar to the algorithm 1 but the median color is replaced by the colors in the matrix M_Θ.

Data: Color C_{med}, run length L, run length matrix M_Θ and list of color in run length matrix C_{M_Θ}
Result: Merge C_{med} and L in M_Θ
initialization : $Delta = 0$, $Deltamin = \infty$, $idx = -1$;
for *i=0:size*(C_{M_Θ}) **do**
    Delta = $\Delta E(C_{med}, C_{M_\Theta}(i))$;
    if $(Delta < JND$ & $Delta < Deltamin)$ **then**
        $Deltamin = Delta$;
        $idx = i$;
    end
end
if $(idx! = -1)$ **then**
    $M_\Theta(idx, L) += 1$
else
    $M_\Theta.add(newrow)$;
    $M_\Theta(newrow, L) += 1$;
end

Algorithm 1: Merge C_{med} and L in M_Θ

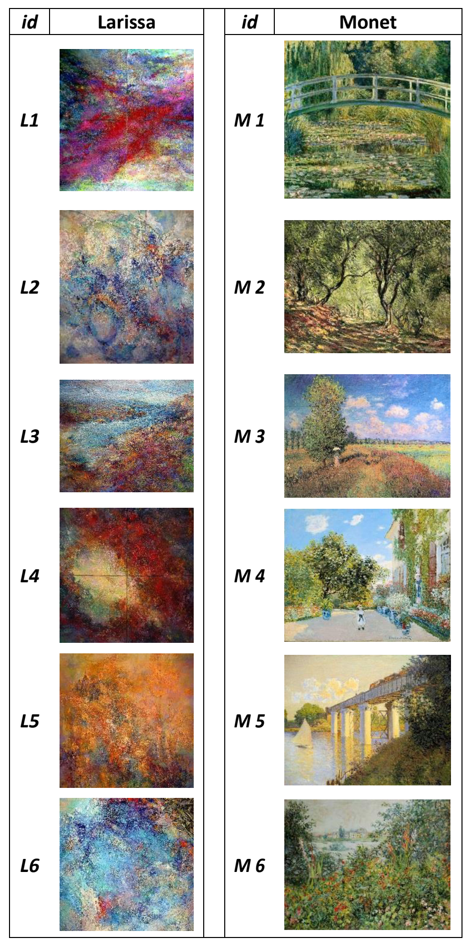

Figure 1. Painting database Part I of II

Application to painting classification

Description of databases

We have tried to characterize by cRLM attributes 4 types of paintings: Miro, DeVinci, Monet and a contemporary artist, Larissa Noury. L.Noury and Monet have an abstract style, Monet is one of the famous impressionist and DeVinci is classical painter of the Renaissance. We can see on Figure 1 and 2 that Larissa Noury's style is closed to the impressionist style because she paints with color touches and with impressions of motions given by her painting applications by hands moving on the canvas.

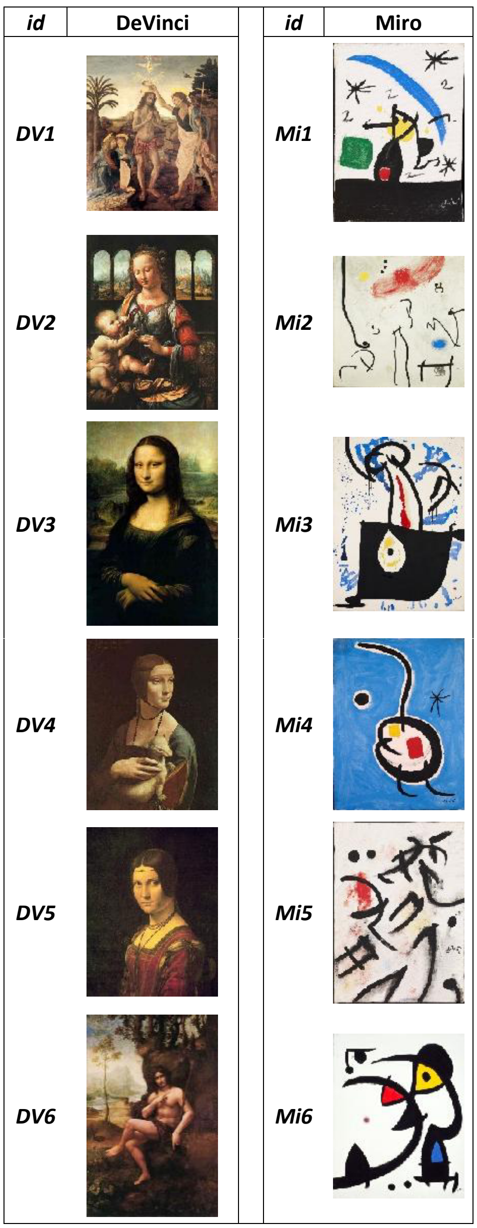

Figure 2. Painting database Part II of II

Used methodology for classification

After computing the global cRLM with a JND value of 4, we extract the 8 features (see Equation 1 to 8), described below, associated to the number of colors on each painting. Then, we used a Principal Component Analysis (PCA) to obtain a visual representation of the position of each painting in the features space. On figure 3, we can note that the paintings of each artist are very closed. They form an independent group regarding the paintings of the other artists. The interpretation of each class and its position is totally linked to a perceptual analysis of the style of paintings. For Miro, we can see that long runs dominate and the color number is very limited. All his paintings forms a really separate class from the others. Despite techniques that may seen almost similar, L.Noury and Monet paintings are closed but clearly separated. Monet's paintings are very aggregated, corresponding to an homogenous style, with quasi constant color number. L.Noury use very different color pallets, of different sizes. The lengths of the runs are very different from painting to another one. That could be explained by the fact that sometimes she applies only small touches of color, and sometimes she spreads the colors with her fingers, giving greater runs. However, her paintings form a single distinct class. DeVinci is very constant through his works. He uses very few colors with medium run lengths. His class is the most aggregated.

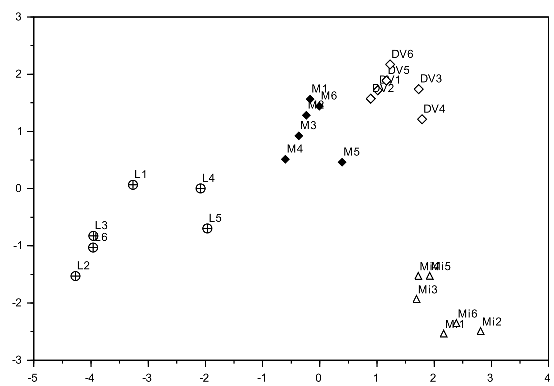

Figure 3. Paintings classification, visual representation of PCA.

Conclusion

In this paper we have proposed a new definition for the color Run-Length Matrices (CRLM)taking into account a perceptual point of view by using JND and ΔE distance in $CIELab$. By computing usual associated parameters, for an application of paintings classification, we show that this cRLM can be helpfully used for textures characterization. Tests have been applied to 6 paintings of 4 different artists with success. After these good results, we can consider to use this color approach in another domains as industrial vision to classify other color textured objects.

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