Automatic color patch selection for painting identification

A.C. Legrand(1) ; V.Vurpillot(1) ; A.Tremeau(1) ; R.Schettini(2) ;
(1) Ligiv Laboratory; Saint Etienne ; France ;(2) IVL, University of Milano-Biocca, Milano, Italy

Abstract

A new method to define a digital signature of a painting is presented. This signature is composed by a set of patches that are automatically selected as the images regions containing the most relevant information.

The region selection is applied on a combination of saliency maps related to different features concerning intensity, color and visual saliency. We present the generation of the feature saliency map exploiting low-level feature representations, and the new algorithm for selecting the most relevant regions. The position and actual size of these regions is not a-priori fixed but is function of the saliency maps, i.e. of the painting content.

We present the experimental results on several painting, discussing the trade-offs among image features parameters values and the selected regions.

Introduction

Many projects are carried on accurate paintings digital acquisition purposes [1] [2]. We present a method working on the final color images that performs selection of the most interesting regions of a painting in order to further make it possible to identify and to characterize a painting by its content.

This work aims to perform an automatic selection of the interesting regions, which has to be adaptive to the relative richness of the image content.

The signature of a painting is defined as salient parts related to the image content itself (radiometric signal) and to the human visual perception. These salient parts are extracted from a combination of feature maps (Figure 1).

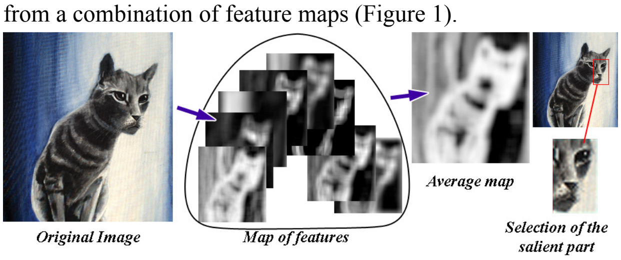

Figure 1. *General principle for the selection of a salient region*

The construction of these maps is firstly presented, with a description of the features and their representations selected to characterize the richness of a painting. The method for the selection of the salient regions from these features is then exposed and results are presented and analyzed.

Image description

Being an automatic area selection, the method uses features in a large field of application, in order to cover the large set of existing paintings styles and techniques. The patch selection is applied on a combination of saliency maps related to different features concerning intensity, color, texture and visual saliency. The general approach to compute these maps is illustrated in Figure 2.

A spatial "saliency" map is calculated for each feature representation, with neighbour consideration. Each pixel of the image is associated a 37-dimensional feature vector composed by: a 7-dimensional feature vector related to intensity, a 26-dimensional feature vector related to color (RVB, rvb, HS, CbCr), and a 4-dimensional feature vector related to visual saliency.

Figure 2. *General principle of feature map computation: for each pixel position, a neighbour is defined, the feature is computed using the neighbour influence, leading to one pixel value in the final feature map (see on the right)*

Selected Features

Intensity feature representations

Intensity feature representations are computed from the average of three color plans, following the conversion from RGB to HIS color space.

One feature derives from the intensity histogram. Three features are computed from smoothness, uniformity and entropy of grey levels [3]. The complexity of a patch is qualified by a high variety (*UI*), a high non-smoothness (*SmI)*, and a high randomness (*RandI*).

The intensity texture richness is represented by three Haralick features [4, 5] from GLCM (Grey Level Cooccurrence Matrix)[6]: non-uniformity feature (*UGLCMI),* non-homogeneity (*HGLCMI*), and local spatial diversity (*CGLCMI*). One intensity texture applies to the edge richness content (*EdI*) from the Canny detector [7].

Color feature representations

Color features are computed from each normalized color plan, and combined to get one grey level map [8]. The map is obtained by calculating the length *VL* of vectors resulting from the three plans of the feature map, R_{feat}, G_{feat} and B_{feat} (Equation 1):

$$VL(i,j) = \sqrt{R_{feat}(i,j)^2 + G_{feat}(i,j)^2 + B_{feat}(i,j)^2} \qquad (1)$$

An overview of a final set of representation maps is given on Figure 3.

Color feature computation is applied for different representations : histogram (*UC*, *SmC*, *RandC*), GLCMs (*UGLCMC*, *HGLCMC*, *CGLCMC*), and edges computation (*EdC*).

One feature characterizing the color variety (CV) is computed from the color histogram [8].

One color characteristic describing the local variation richness of the color texture (*SpVarC*) derives from a tool used by Cutzu (Equation 2).

$$SpVarC = \underset{k=R,G,B}{VL}\left(\underset{(m,n)\in patch}{mean}\left(abs\left(Lap_k(m,n)\right)\right)\right), \quad (2)$$

where Lap_k is the plan k filtered with the Laplacian filter.

One color feature characterizes color contrast, based on a tool developed by Schettini [9] (Equation 3):

$$Col_{Contrast}(x,y) = \frac{2}{\pi}\arccos\left(\frac{c(x,y)\bullet c_{mean}(x,y)}{\|c(x,y)\| * \|c_{mean}(x,y)\|}\right) \quad (3)$$

The final representation map (*CCont*) is the result of a mean filter applied to the linear combination of both color and intensity contrast images.

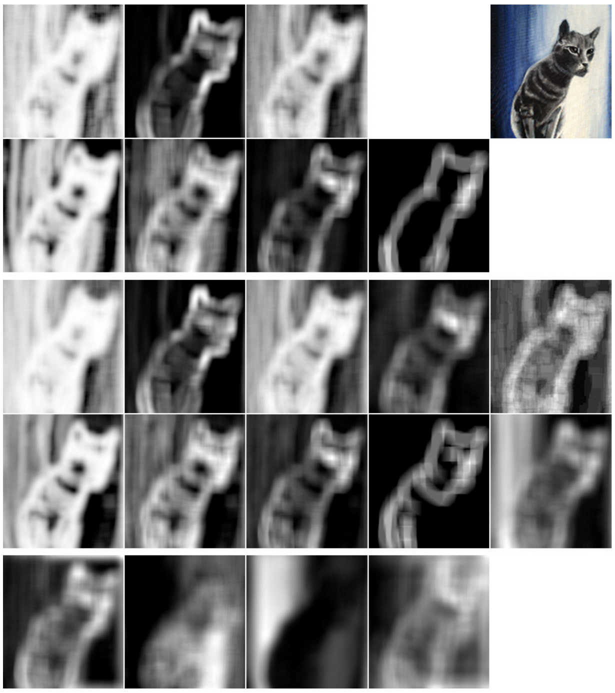

Figure 3. *Final set of representation maps, for an initial patch of 10% of the image: 7 intensity maps (UI, SMI, RandI, UGLCMI, HGLCMI, CGLCMI, EdI) followed by 10 color maps (UC, SMC, RandC, SpVarC, CV, UGLCMC, HGLCMC, CGLCMC, EdC, CCont), and 4 visual saliency maps (IntCont, RGCont, BYCont, OrCont)*

Visual saliency feature representations

Because the human visual system is more adaptive to the context than to absolute values, some representations also model this way of perception : contrast perception (on intensity, color or orientations). Our representations (*IntCont*, *RGCont*, *BYCont*, *OrCont*) derive from perceptual saliency maps developed by Itti [10].

Feature selection

To select the most relevant features, correlation between the 37 features described is achieved. Redundant features are removed. Table 1 describes the reserved features. These features and the representation space to which they applied have been chosen so that their corresponding map of interest are the most possible decorrelated one from each other, when considering a large set of images.

Final achievement

Patch selection

The final result consists in one map by feature representation. To extract the most salient parts of the image, different combinations of the maps were carried out. These combinations were based on statistical and classification criteria (arithmetic mean, weighted average, PCA, successive maxima selection). The final combination is based on contrast analysis of feature maps, all maximum of feature maps are studied and selected if the saliency contrast is important.

Table 1. Overview of selected features.

Descriptors	*Based on the work of*	*Representation Space*	*Characteristics*
Color spatial variation	*Cutzu 2005*	RGB, HS, CbCr	Detects strong color variations
Number of unique colors	*Cutzu 2005*	RGB	Measures color variety by counting the number of representative colors
Color contrast	*Schettini 1996*	RGB + I	Real color texture descriptor (color vectors orientation and length)
Histogram smoothness	*Gonzales 2003*	I, rgb, HS, CbCr	Describes standard deviation of pixel values
Histogram uniformity	*Gonzales 2003*	HS	Describes non-uniformity of pixel values
Histogram randomness	*Gonzales 2003*	I, CbCr	Describes randomness of pixel values
GLCM Uniformity	*Haralick 1979*	I, rgb, HS, CbCr	On 4 orientations, measures image texture non homogeneity
GLCM Contrast	*Haralick 1979*		On 4 orientations, measures image texture contrast
Contour	*Canny 1986*	I, rgb, HS, CbCr	Measures the density of strongest edges
Intensity visual contrast	*Itti 1998*	I	Results in the mean of maps computed for two scales of perception
RG and BY visual contrast	*Itti 1998*	r,g,b,y	Results in 1 map per color contrast channel (rv, by), mean of two scales
Orientation visual contrast	*Itti 1998*	I	Computed on 4 orientations, results in the mean of two scales

Results and analysis

The method proposed combines saliency maps related to intensity, color, texture and visual saliency to cover the large set of painting styles and techniques. Results were analyzed according to painting styles and techniques and to computation parameters of saliency maps.

We present in this paper results analysis compared with visual perception methods of saliency maps construction, such as Itti method. The Itti method is based on a modelisation which is the method reference in the context of visual saliency.

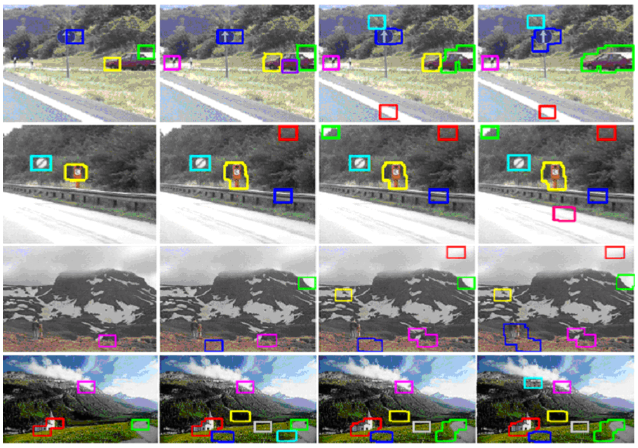

Figure 4. *Image areas selection for different method parameters*

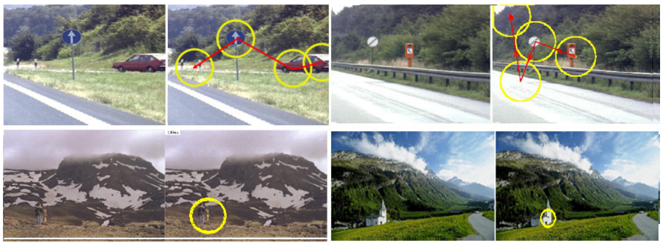

Figure 5*. Image areas selection by Itti method (original- salient areas)*

Figure 4 and Figure 5 present the resultsof Itti method and our method for differents parameters adjustement. The extracted regions and the extraction order were compared with Itti method results.

These results show that Itti areas are also detected by our method. But by our method, other salient areas are detected with a different content of information: the saliency is not restricted to perceptual aspects. Moreover, our method performs well in dark regions: some salient regions are detected by our method and not by Itti method. This performation is explained by the different representations of the selected features: the different color components (hue, saturation, Cb, Cr) bring out areas with a great information value and a not very important visual apparence.

Our method combines several kinds of features which enable to characterize the richness of an image either in terms of perceptual features such as lightness, color, edges, either in terms of signal features. This variety allows detecting salient parts in a large field of application and especially in a large setting of existing paintings styles and techniques whatever the analysis task.

The application objective is to define a signature of a painting in order to authenticate it. Actual and future works are focused on this signature definition from these extracted salient parts. The method has to test in a large data base of works of art (styles, techniques) and to analyze in different conditions and according to parameter influence.

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Author Biography

Anne-Claire Legrand received her Phd in signal and image processing from Burgundy University, France (1998). She is involved in Ligiv laboratory, University of Saint Etienne, France. Her research interests are focused on spectral imaging and colour science for digital acquisition. She works on design and evaluation of similarity metrics for spectral imaging.