2D artistic images analysis, a content-based survey

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Automatic artwork analysis techniques are used in numerous image-based applications such as virtual restoration, image retrieval, studies on artistic praxis, authentication etc. This paper first presents a comprehensive survey on 2D artworks analysis for the past ten years. Following a content-based taxonomy, we organize and discuss the literature from low-level features to several high-level layers of concepts. We finally open the discussion with several issues, from cognitive processes implied in the creative process that induce some visual cues, to expressive rendering which is a related research fields that shares the same concerns as artwork analysis.

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1. INTRODUCTION

Cultural institutions around the world have, over the past two decades, implemented a policy of digitally safeguarding in part or full their artwork collections. These institutions were initially supported by important research projects on digitization systems able to set some high quality standards such as VASARI [Martinez et al. 1993] for visible lighting conditions or CRISATEL for multispectral digitization. The primary goals of the cultural institutions are the digital preservation of artworks and the monitoring of their condition, as well as improving accessibility to collections, targeting both expert and inexperienced audience. This policy has led museums to build large image databases of artworks, sometimes available on the Internet with variable image resolutions (e.g. the online graphical art image database of the Louvre contains 150000 drawings [Louvre 2009]). The DELOS-NSF working group on Digital Imagery for Significant Cultural and Historical Materials published a manifest to stress the great interest in investigating automatic analysis and understanding of cultural heritage pieces of work [Chen et al. 2005] and to point out that this domain is at its early stage. Among the recommendations that are issued by this working group, the need for methods that automatically analyze artworks is stressed under the scope of mining digital image repositories. The urge for bridging the gap between the physical content and the meaningful content in artworks is also mentioned.

Numerous applications have to consider fully or partially some artworks analysis techniques: e.g. image enhancement for publication purposes, virtual restoration

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of artworks (inpainting, fading color enhancement, crack removal, etc.), content based retrieval of artworks in databases, image-based 3D reconstruction (sculptures, archaeological sites, etc.), specific artist studies (color palette statistics, creative process, etc.), art history investigation, authentication, watermarking, expressive rendering (render a stylized drawing from a 3D object for animation purposes, etc.). In each of these applications, user-needs have to be considered and may influence the technical constraints [Chen 2007].

Growing research interest in the field is stressed by several scientific journals devoted to this research domain (ACM Journal on Computing and Cultural Heritage, Journal of Mathematics and the Arts), special issues published in more general journals [Cappetellini et al. 2004; Barni et al. 2008; Postma et al. 2007; Charvillat et al. 2009], regular conferences (EVA's conferences, Museums & the Web, Eurographics Computational Aesthetics, CHArt, etc.) or dedicated programm tracks [Stork and Coddington 2008; Stork et al. 2010], working group (DELOS/NSF, digital painting analysis group [Group 2009], etc.) or technical committee (IAPR TC19). Four surveys have been published on the period that goes from 1990 to 2000 [Cupitt and Martinez 1994; Martinez et al. 1997; Maitre et al. 2001; Martinez et al. 2002]. More recently, two surveys deal with the specific task of image retrieval in cultural heritage digital libraries using metadata [Mattison 2004; Tsai 2007], one survey on applications [Bartolini et al. 2003], and one survey deals with virtual museum issues [Styliani et al. 2009]. Stork [2009] proposed an introductory survey of papers focusing on art history problems.

This paper focuses on previous works involving automatic artwork analysis in partly or fully. To the best of our knowledge, this is the first survey dedicated to computing techniques applied to 2D artworks analysis, not focusing on a specific application and dedicated to the last decade. The sources of the literature on this subject is heterogeneous and hard to follow. Two reasons can explain this situation: financial supports are thinly distributed, and as in new research areas, involded scientists come from heterogeneous origin. Yet, the situation is changing and the domain becomes more mature. A broad set of classical techniques have already been investigated. This transverse survey allows research scientists to discern what, and how techniques have already been used in different research areas. As for medical imaging, artwork analysis techniques are becoming more and more specifically designed for this type of image. Visual artworks are often stylized, and this style perturbs many of the a priori that could be used in natural images understanding.

Metadata is the classical, and today still practical, approach to describe an artwork and index a database. Two surveys dealing with artworks retrieval using metadata can been found in [Mattison 2004; Tsai 2007]. One of the main constraint of metadata is the need to manually capture most of these data. It has been shown that this manual task present a low coherence between indexers [Mai 2000]. Besides, metadata uses words to describe features. They are thus well suited to some factual information such as the artist's name or the creation date. Practical recent systems intend to combine metadata information given from museums and content-based features [Lewis et al. 2004; Vrochidis et al. 2008]. Metadata are commonly captured by curators in museum databases. A recent strategy that concerns more subjective metadata is to use the social annotation (also called folksonomy) from public websites combined with an ontology [Leslie et al. 2007]. More subjective information dealing with cultural abstraction or spatial relationships for instance are far much difficult to capture with metadata. These types of information thus offer a great potential and challenge for automatic techniques as we will explore in this survey.

Previous works can be organized following the different categories of image content. Inspired by the taxonomy given by Burford [2003], we propose to organize the literature using the structure visible in Table I. This taxonomy is ordered along the levels of abstraction of the image content. Perceptual primitives such as colors are the lowest level of abstraction. As a general rule of thumb, we classified the papers in each category depending on what aspects does the paper emphasize its scope. For instance, some of the presented early papers in the first category uses several perceptual primitives, and test them under a database classification framework separating several artists. We chose not to put this type of paper in the cultural abstraction category which contains some previous works whose goal is clearly to characterize the personal style of some artists.

Table I. A taxonomy of image content, inspired from Burford et al. [2003].

	Category label	Notes and examples
Image-space Sec. 2.1-Sec. 2.4	Perceptual primitives	Color, texture, local edges
	Geometric primitives	Strokes, contours, shapes
	2D relationships	Spatial arrangement of objects in the image, composition
	Semantic units	Names of the objects, general (e.g. horse) or specific (e.g. Eiffel tower)
Object-space Sec. 2.5-Sec 2.6	3D relationships	3D arrangement of objects in a scene, perspective, depth cues
	Contextual information	Illumination, shadows
Abstract-space Sec. 3	Cultural abstraction	Aspects that can be inferred using specific cultural knowledge: artistic style
	Emotional abstraction	Emotional responses evoked by an image: affective computing
	Technical abstraction	Aspects requiring specific technical expertise to interpret: authentication, cracks, drawing tools

Following, this taxonomy, we organize and discuss the literature in the two next sections. In Section 2, we focus on screen-space and object-space contents, from low-level perceptual features to semantics. In Section 3, we gather all the abstract categories which tackle different layers of content than the semantic content. Section 4 extends the discussion with several related fields, from cognition implied in the artistic process that induces some visual cues, to expressive rendering which is a related research community that shares the same concerns.

2. FROM PERCEPTUAL PRIMITIVES TO SEMANTIC UNITS, THE SEMANTIC GAP STAIRWAY

In this section, we go up the stairs of the attempts to bridge the semantic gap. Color, texture and edges are the first features that can be extracted in an image. Many of the higher steps rely on these features. Whereas in natural images, color and texture by themselves are of high interest in artworks. Some artist's artworks can be strongly characterized by their color palette or the texture of their strokes. Spatial relationships are the next classical step in order to structure the low-level information.

2.1 Perceptual primitives

2.1.1 *Color.* Color content is one of the important pictorial tools available to artists. As a spectator, we are also highly sensitive to color in artworks. Colors are usually described in a chosen color space. Depending on the targeted application, numerous color spaces were developed. RGB space is suited for Television and computer screen due to its additive colors model. CMYB space is designed for printing, using a subtractive colors model. HSV (Hue, Saturation, Value) offers intuitive controls to manipulate color and is thus usual in computer graphics programs. CIE Lab and Luv are psychometric spaces which are perceptually uniform at low distances. These two last color spaces are therefore very frequent in the literature discussed in this survey.

A classical pixel-based and image-analysis approach would be to consider an artwork image as a collection of individual pixels whose color is defined in a specific color space. Thanks to their computational advantage, histograms did encounter a relative and early success to model the image content. The color histogram can thus be computed as an approximation of the color distribution. It gives a simple and compact representation of the color content of an artwork. This representation has been intensively used in image retrieval systems, e.g. [Kushki et al. 2004].

Instead of considering all colors appearing in an image, many papers tend to reduce the number of extracted colors. This type of approach is sustained by the fact that artists use a limited set of colors in their palette. From a linguistic point of view, we also a have a limited set of words to name colors [Brent and Kay 1969]. Several papers are based on the Itten colorimetric categories [Corridoni et al. 1998; Stanchev et al. 2003; Yelizaveta et al. 2004; 2005], Hering theory of complementary colors [Lay and Guan 2004], Berlin and Kay categories [Chang et al. 2003], or an adaptive reduced palette using Dominant Color Description [Kushki et al. 2004] or principal component analysis [Barla 2006]. Basically, a segmentation step such as a K-mean algorithm [Corridoni et al. 1998; Stanchev et al. 2003] or more sophisticated methods such as Blobworld [Yelizaveta et al. 2004; 2005] or Mean-Shift [Barla 2006] constrains the spatial coherence of colors.

Using Gabor filtering, complementary colors transitions inside Van Gogh corpus have been investigated as part of the now-ended *Authentic* project [Berezhnoy et al. 2004; 2007]. This academic project investigated new image analysis techniques which could be applicable for the assisted analysis of visual art forgeries.

2.1.2 *Texture.* Local texture effects although they are low-levels features, are also a very intuitive tool available to artists. Style of some artists such as Monet or Pollock is mainly based on the texture of their brushtroke patterns. As we will see in Section 3.3, it is often hence used in technical abstraction approaches to authenticate artworks from several specific artists.

Including some texture features in histograms is not straightforward. Pass et al. [1997] proposed the so-called color coherent vectors (CCV). For every color in an image among a discretized colorspace these histograms include the proportion of pixels having this color and belonging to a coherent region, that is a region whose pixels are not separated by a connex spatial path longer than a threshold. Similarly, color can be characterized by some other information, such as the local gradient module in the joint histograms of Pass and Zabih [1999]. In Huang et al. [1997; 1999], Haralick cooccurrence matrices are named correlograms. Every color of these histograms contains the probability to have a pixel of the same color (autocorrelograms) or a different color (general correlograms) at a spatial distance lower than a fixed threshold. Autocorrelograms combined with the gradient module have been investigated in Williams and Yoon [2007].

Image decomposition filters have also been extensively used to study the local organization of pixels, such as Discrete Cosinus Transform [Keren 2002; 2003], wavelets [Lewis et al. 2004; Kobayasi and Muroya 2003] and MPEG-7 standardized use of Gabor filters [Kushki et al. 2004]. Due to their solid mathematical foundations, these decomposition filters offer robust analysis tools that are often used towards technical abstraction (e.g. authentication, individual artist studies, ...) as we will see in Section 3.3 which contain many more techniques relying on color and texture analysis.

2.2 Geometric primitives

The geometric primitives in artworks are the contours of drawing strokes, painting brush strokes and by extension the shapes of the depicted objects. Among the panel of primitives that are visible in artworks and considering artists' technical and educational constraints (line-drawings is a basic and fundamental course), geometric primitives offer a natural feature to analyze in artworks. They are the straightforward marks left by a pen, a brush or most of the tools that are used by artists. Two related research fields are cursive handwriting and technical drawings analysis.

Cursive handwriting analysis sounds very close to line-drawings analysis, and is quite a mature research domain. Therefore should we clarify the differences between those two scientific problems. The neuro-biomechanical process implied in both tasks are very similar. Cursive alphabets are kind of line-drawings, and sometimes can be considered as such. Yet, writing inherits several geometrical constraints. Alphabets variability is bounded to a list of characters which have more or less the same size and spatial frequency. One of the biggest difficulties in writer recognition is the allograph variability. This means that a same letter can be written using a limited list of different symbols. The line *alphabet* of an artist is however infinite. The cognitive process of drawing and writing are also different. Writing is a spontaneous task involving no continuous judgement of the writer [Schomaker 1991] whereas an artist has to continuously analyze his drawing while doing it [Van Sommers 1984]. Besides, handwriting tend to produce images where strokes are quite isolated whereas overlapping strokes is more likely to occur in artistic images.

Similarly, analysis of technical drawings such as maps and engineering drawings has also received considerable attention during the last decades [Tombre and Chhabra 1998]. Next open issues in this field are presently vectorization and symbol recognition of handmade sketchy drawings [Tombre 2006]. Presently, vectorization techniques are often applied to binary images and this problem classically deals with the recognition of two different pattern: straight lines and circular arcs. Junction reconstruction is also a major issue. Interestingly, cultural heritage documents have been recently stressed as being one of the next emerging topic of interest by this community for indexing applications [Tombre 2006]. Dealing with artistic images, we cannot rely on some geometric a priori as in the technical document analysis field. Artistic drawings present a wide variety of regular to non-regular primitives.

Considering artistic drawings, extracting the strokes is a difficult problem. Hurtut et al. [2008] propose a parameterless method to extract the boundaries of strokes from the set of level-lines in the grayscale image. Level-lines of an images are defined as the connected components of the topological boundary of the so-called image level sets. This topological definition let group the strokes boundaries in a hierarchical tree that reflects the topological relationships in the drawings. This approach is yet not robust to dense overlaps which is the major issue when we want to extract the original stroke path from offline images. Lettner and Sablatnig [2008] tackles that issue and propose a thinning and following algorithm to reconstruct the original drawing traces of painted strokes. Disambiguation at junctions is solved using the Gestalt *good continuation* principle as in Plamondon and Privitera [1999] for cursive handwritting. The same principle and Hough transforms are used in Remi et al. [2002] to extract strokes in online constrained line-drawings in order to detect possible children neuro-biomechanical dysfunctions.

Painting strokes have also raised a number of studies. Berezhnoy et al. proposed a method using a circular filter to extract brush strokes which are then either interpolated by a third-degree polynomial function [Berezhnoy et al. 2005] or estimated by a multilevel thresholding [Berezhnoy et al. 2009]. These approaches are adapted to very small and often isolated strokes such as Van Gogh's. Shahram et al. [2008] also take advantage of Van Gogh's style and propose a statistical approach to simulate an iterative recovering of the brush strokes layers. Layers are successively peeled off, ordered by the standard variation of their spatial statistics. The recovering is simulated by using an inpainting technique. An interesting approach to extract strokes have been proposed in the Non-Photorealistic Rendering literature, which is a Computer Graphics research area (see Section 4.3). In Xu et al. [2006], the key idea is to use a brush stroke library to fit vectorial strokes on Chinese paintings which are oversegmented by a Mean-Shift algorithm. Regions are merged using the a priori that color gradients are low along brush strokes. This approach is again well-suited for artworks where strokes are sparse but it seems more robust and versatile than other approaches.

Extracting overlapped strokes is somehow an unfeasible problem in most offline images and especially paintings. Therefore, some papers do not endeavour to retrieve the underlying paths. Instead, and depending on the application, one may consider pixel-based approaches to analyze geometric primitives. Brush strokes analysis then becomes equivalent to texture analysis. Towards that goal, several approaches have been proposed (developped in Section 3.1 and Section 3.3) using wavelets [Li and Wang 2004; van der Maaten and Postma 2009] or textons [Varma and Zisserman 2003].

2.3 2D visual relationships

2D visual relationships relates to the spatial organization of objects or homogeneous regions in an image. It is an important intermediate feature between low-level content and image semantics which is still an active research well beyond cultural heritage concerns. Two kinds of spatial relations can be discussed: *absolute* and *relative* spatial relations.

Absolute relationships. The absolute spatial organization targets the global position of regions regarding the overall artwork background. It is one of the first aspect to be perceived. It is also related to the concept of visual balance as studied by Arnheim [1954] (see Section 4.1). In the cultural heritage domain, it models the artistic composition [Chen 2001]. Such feature can be used for illustration, generation of ideas, aesthetic decoration, and learning [Conniss et al. 2000]. Image retrieval using the absolute spatial organization of colors can be serendipitous, meaning one can accidentally discover a fortunate association of semantically different images delivering the same visual impact, which is practically impossible using metadata or ontology-based description.

An early approach is the well-known QBIC system proposed by IBM in 1995 which has been sophisticated in 1997 by integrating some spatial information [Holt et al. 1997; Bird et al. 1999]. The image is partitioned into 108 squared regions, which is equivalent to an extreme downsampling. An image is modelled by the spatial locations and the colors of the pixels of this downsampled image. The QBIC system is designed for image retrieval tasks. Therefore a similarity measure has to be defined to compare the spatial organization of two images. This point is essential and might be as important as the image model. The similarity measure defined in the QBIC system is a least square distance between pair of pixels. QBIC is still used at the the Hermitage museum in St. Petersburg. A similar approach [Hurtut et al. 2008] also use downsampled thumbnails, yet combined with a more sophisticated similarity measure called the Earth Mover's Distance. This distance is directly computed on thumbnails and can handle matchings between non-connected regions. It is also known to be close to human perception for small color distances [Rubner et al. 2000].

In Tanaka et al. [1999; 2000], the geometrical analysis of the academic composition of past artworks helps to assist some CAD tasks. This tool extracts the dimensions and locations of the different homogeneous regions in an image using an edge-flow segmentation method. Regions are filtered using several criteria on contrast, texture and color information. The artistic composition is then analyzed based on visual balance rules. This approach is yet limited by this set of rules (e.g. gold ratio). Similarly, in Corridoni et al. [1996; 1997], the authors propose to match some low-levels information such as color and spatial location with several high-level concepts such as temperature and visual harmony inherited from Itten [1961]. There are some drawbacks when attempting to close the semantic gap between low-levels features and any sets of high-level concepts such as chiaroscuro.

First the performance is limited to the number of concepts which not always reflects some real artistic ground truth besides art history. By definition, these concepts are also explicitly dependant on the low-levels features extraction and selection.

Relative relationships. Relative spatial relations provides strong information to enrich the low level representation of the visual image content. Considering that homogeneous regions or symbolic objects have already been extracted, we focus here on how to model or characterize the spatial relations between them. That is for instance that object A is under and on the left of object B (see the seminal work of Freeman [1975]).

An artwork retrieval system called PICASSO has been proposed in Del Bimbo et al. [1998]. The authors use a multi-scale segmentation scheme that enables the user to choose its query among different scales of details in the image. The biggest scale corresponds to the whole image. Smaller scales let query the database with some specific regions or represented objects depending on the segmentation success. This multiscale scheme let group the regions in a hierarchy graph, where each node represent a region, coupled with several descriptive features. The similarity is a minimal cost distance between two graphs which does not support the matching of non-connected regions. A more sophisticated distance called weighted walkthroughs capturing the spatial organization of sets of pixels has also been proposed [Berretti et al. 2003].

Delaunay triangulation is a convenient way of representing local spatial relations. Expressive Rendering (Section 4.3) has investigated its use on vectorial artistic textures [Barla et al. 2006; Ijiri et al. 2008]. This representation seems efficient to render regular to near-regular textures by example. In order to capture near-regular to random textures, Hurtut et al. [2009] proposed to use a statistical approach based on marked point processes. Yet, this representation is limited to stationary textures

Another direction is to model the spatial distribution of strokes, small objects or peculiar cues. One of the paper that studies spatial organization of 1D stroke elements in artistic and technical drawings can be found in Onkarappa and Guru [2007]. The spatial distribution of objects is constructed by using a symmetrical matrix gathering their pairwise relative positions. The relative positions are expressed according to a 8 directional quadrants (North, North-East, etc). They also define a similarity distance between two matrices to enable line-drawing retrieval in a database. Cromwell [2008] studied the distributions of knot types in interlaced ornament. This approach relies on the mathematical background of the knot pattern theory.

The artistic composition modelled by the absolute relationships is a quite specific aspect, yet high-level, of artworks. Relative relationships targets more applications and has a stronger impact on the effort to bridge the semantic gap. This research problem is thus logically studied by many scientists beyond the cultural heritage scope. Recent works should therefore be investigated towards that goal, see for instance an approach proposed by Punitha and Guru [2008] based on B-tree. In Petrakis [2002], attributed relational graphs (ARGs) are compared with symbolic projections (2D strings) which are two major techniques. Depending on the scope, we can also choose between a qualitative or a quantitative description of the relationships.

2.4 Semantic units

Semantic units relates to the descriptive content of an image and thus highly suffers from the so-called *semantic gap* between low-level features and high-level concepts [Lew et al. 2006]. The semantic gap is larger in visual arts images than in natural images since artworks are most often not perfectly realistic. The depicted reality of artists is also highly variable.

One of the paper that attempts to automatically characterize the semantic units in artworks uses SIFT descriptors and an image retrieval framework [Valle et al. 2006]. Nowadays, SIFT descriptors have a great success for object retrieval and exact matching tasks thanks to their robustness [Lowe 1999]. Valle et al. apply these descriptors on grayscale images, and their method seems indeed efficient to retrieve duplicated images from a query that could have been altered (linear transformation, noise, etc.). Another study focuses on cultural relics over homogeneous backgrounds using existing semantic annotations, computational visual features and a relevance feedback loop [Ren and Wu 2006]. Similarly in [Maghrebi et al. 2007], the authors endeavour to combine some manual annotation and computational descriptors based on shape and the Curvature Scale Space applied to the manually extracted contours. This approach is evaluated on ancient paintings.

To resolve the lack of ideal set of features, Yen et al. [2006] investigated the use of the Adaboost algorithm. This approach initially uses a set of 4356 classical texture-based features. Then, by using a several weak classifiers, the method selects and combines the most discriminant features according to a manual ground truth and the chosen query image.

Line-drawings databases include for instance logos, technical documents, patent graphs and graphical art. Due to their limited size of color palette, watermarking embedding techniques cannot be applied. Sun and Kise [2009] proposed a fast method to detect full or partial illegal line-drawings in big databases. Their method use stable extremal region detection, histogram of orientations and a hash table for speedup.

Several methods have also been proposed in the context of interactive guide systems for the recognition of artworks in museums (see e.g. [Fasel and Van Gool 2007] using SIFT descriptors). These systems let the visitor interactively find more information on artworks using a kind of video guide. This guide uses a small web-camera combined with a pattern recognition system that matches the picture taken by the visitor with the museum database.

Although the topic of research of exact matching between images is not specific to cultural heritage, it is often a major concern of cultural institutions due copyrights constraints. It thus still constitutes a promising research field that will attract attention from both domains.

2.5 3D visual relationships

3D visual relationships relates to the 3D spatial organization of objects in a scene represented on a 2D image. Perspective and 3D visual relationships in general is thus very close to scene understanding and 3D reconstruction. This content category and the following is closer to the object-space or scene-space than the previous ones. We will see in Section 4.2 that perspective and depth issues in artworks can be characterized in many ways [Willats 1997; Livingstone and Hubel 2008].

Vanishing points are important hints of the 3D structure and the perspective of a scene. A parameterless method to detect vanishing points without any a priori information is proposed in Almansa et al. [2003]. This approach is tested on several Renaissance paintings. It relys on the detection of a sufficient number of meaningful straight lines in the image. Criminisi and Stork [2004; 2005; 2006] explored many aspects of perspective by Renaissance masters in response to the Hockney-Falco theory. Hockney and Falco thesis is that some Renaissance artists might have used lensed-based optical systems to render complex 3D objects [Hockney 2001]. This thesis has been very controversial and provoked a long list of pro- and con- research papers.

These previous works first focused on perspective projection systems which corresponds to our natural vision system. Yet artworks can be based on several other *drawing* systems such as orthogonal, horizontal/vertical, oblique or naive projection systems [Willats 1997]. Art history illustrates this wide diversity of possible systems that are used by artists. Characterizing these different drawing systems is a challenging future work. Tonder proposed to measure the level of perspective and spatial composition in Japanese paintings of gardens [van Tonder 2007] showing that this measure differentiates several classical landscape painters.

Another issue is to enable single-image based 3D reconstruction. El-Hakim [2001] proposed an early approach to reconstruct 3D scenes from paintings based on several constraints related to coordinates, surfaces and topologies in the image. This issue opens a wide range of applications aimed at Museums. The same kind of methodology can also be used to reconstruct 3D model of cramped scenes (e.g. interior of small temples) where multiple distinct points of view cannot be collected easily.

Considering object space issues in general, Computer Graphics literature offers a source of inspiration for artwork analysis problems. *Visibility* for instance is a major concern. See Durand [2000] for a detailed survey of visibility inference.

2.6 Contextual information

Contextual information in artworks are all the cues related to illumination such as shadings and cast shadows. Both participate to the perception of depth. An early approach deals with cast shadows of skin patches in Renaissance portraits [Widjaja et al. 2003]. Color profiles at silhouette regions are averaged and feed a SVM classification scheme in order to recognize different painters.

Inferring the illuminant direction and location from cast-shadows is possible as soon as a point on a cast-shadow can be matched with its corresponding point on the occluding contour. When the cast shadow is not available, it is a more challenging problem. Stork and Johnson [2006] tackle this problem in realistic paintings. The authors make use of a computer-vision algorithm that estimates illumination direction based solely on a 2D occluding contour [Nillius and Eklundh 2001]. This approach assumes that the illuminant is a point source and that the surface are uniform Lambertian. Different estimations should lead to a single point of convergence. Yet this might not be true in artworks since artists often manipulate physical laws locally. Therefore Stork et al. propose a maximum-likelihood criterion that integrate estimates from multiple occluding contours. In Johnson et al. [2008], a 3D model-based approach is used to infer illuminants using simple objects in the image such as the eyes or a pearl pendant.

As for 3D relationships, Computer Graphics has seeded a great amount of investigations dealing with contextual information inference and analysis. A good introduction to standard computer graphics techniques can be found in Foley et al. [1995].

3. THE ABSTRACTION GAP

We discuss in this section many previous works focusing on abstract aspects that are specific to art images. These issues are different from the semantic challenge. A first impression could be that these issues should be more difficult than the semantic recognition of the scenes. As we will see, some of them might actually be simpler since they rely on preattentive layers that occur prior to the recognition process.

3.1 Cultural abstraction

Cultural abstraction relates to information inferred from cultural knowledge. Artistic style analysis belongs to that category and is the content on which this section focuses. Artistic style inherits from many definitions and thus can be considered as an ill-defined concept when tackled from the computer vision perspective. According to the American Dictionary [Pickett et al. 2000], style is "the combination of distinctive features of artistic expression, execution or performance characterizing a particular person, group, school or era". We adopt this definition here and thus consider style in an image-based sense, rather than an artist-centred sense. Papers that restrict to a specific artist or which aim an authentication task will be discussed in Section 3.3 which focuses on technical abstraction.

An early study attempts to characterize the *visual signature* of painters [van den Herik and Postma 2000], which is similar to writer identification and automatic graphology in the document analysis domain. Using a neural network scheme, the authors compare several features such as Fourier descriptors, spatial orientations, gray levels distributions, moments, fractal indices. They conclude that the best features are fractal indices, Fourier descriptors and the mean gray level. This last surprising feature is probably partially due to the small size of their test set made of 60 paintings from 6 different artists. This evaluation scale is a drawback of most proposed approaches in this section, reducing their scope. Limiting a study to just a few styles and a few samples stress first the difficulty to collect some images in the cultural heritage domain, and second the possible lack of robustness.

Several similar approaches are based on a few definitions of some modern art movements such as chiaroscuro, cubism and impressionism combined with a set of perceptual low-level features. These features are generally contrast, color and luminance cues, either using histograms [Nack et al. 2002; Yelizaveta et al. 2004], pixels ratios [Icoglu et al. 2004; Gunsel et al. 2005; Yan and Jin 2006], or wavelets [Seldin et al. 2003]. This last approach differentiates a 35 artworks database involving five different artists, stressing anew a limited evaluation scale. Lombardi [2005] did his thesis on the automatic classification of style in fine-art paintings. During his thesis he studied and compare most of the low-level descriptors that were previously proposed.

Li and Wang [2004] investigate an interesting combination of wavelets features and a supervised classification scheme based on Hidden Markov Models on a 276 Chinese paintings database. This multi-scale framework captures and implicitly mixes both the texture effects and geometric primitives variations which are characteristic features of this kind of paintings. Traditional Chinese ink paintings has also been investigated using Canny segmentation [Zhang et al. 2004], color coherence vectors combined with Sobel edges and support vector models [Jiang et al. 2006], and deformable models [Pham 2005].

Fonts offer an interesting opportunity to study the separation between style and content or the parametrization of style [Hofstadter 1986]. Tenenbaum and Freeman [2000] propose to use bilinear models that separate style and content observations, fitting a bilinear interaction map between them. Dealing with fonts, the authors yet faces the curse of dimensionality and have to use a high-dimensional feature space on very low resolution images. They also use a physical model that ensures visually satisfying linear combination of letters. Several works focus on stylistic features of drop caps letters in enlightened manuscripts [Coustaty et al. 2009] using a letter shape extraction method [Coustaty et al. 2009] based on a Total Variation minimization decomposition [Aujol and Chambolle 2005].

Unfortunately style and semantic depiction share the same visual atomic primitives (lines, dots, surfaces, textures). Manual style recognition is a very difficult task, requiring the knowledge of numerous art historians and experts. An artwork from the blue period of Picasso for instance is recognizable not only because of its blue tonality, but because of many semantic features and iconographical cues. As long as computational methods do not succeed in extracting the representational content of images, the separation of stylistic content will remain out of reach. In order to steer clear of this ill-posed disambiguation, Hurtut et al. [2008] proposed to analyze the *pictorial content* in line-drawings. Pictorial content is defined by the authors as the combination of the artistic style and the visual features formed by the set of strokes composing an artistic line-drawing. Dealing with line-drawings, the pictorial content corresponds to strokes junctions, endpoints, corners, curvature etc. This content targets the preattentive and idiosyncratic effect produced on a viewer watching an artwork (see also Section 4.2). That is the effect prior to any recognition by the visual system of any possible realistic subjects depicted in the artwork. The authors use these features to retrieve similar line drawings according to their pictorial content in two databases gathering 2500 images.

3.2 Emotional abstraction

Emotional abstraction relates to emotional responses evoked by an image. These issues concerns the research domain called *affective computing* which receives widespread attention among computer scientists beyond cultural heritage. It is noticeable that artworks constitutes a type of images that naturally exploits affective effects. Due to their implicit stylization, we do not look at artistic images with the same kind of attention and expectation as for natural images. Datta et al. [2008] gave an exposition on challenges and issues of computational aesthetics and emotional abstraction measurement in photographies. The pictorial content approach presented in last section is also related to this section since this aspect is supported by the pictorial effect delivered to a viewer.

Many approaches in this section endeavour to bridge the gap between selected low-level features and several emotions expressed with pairs of words, e.g. *warm-cool* (see also Section 2.1 with studies using the Itten sphere).

—Colombo et al. [1999] build from perceptual features to expressive features, and finally emotional features such as *action-relaxation*, and *joy-uneasiness*. They support their theory using art images where expressive features are based on lines and pixels colors combined with the Itten sphere. Using a compositional semantics framework, that is some compositional rules between features, they build on these features to compute emotional features.

—Histograms of edge orientations are used to categorize *static-dynamic* drawings in Wei-ning et al. [2004]

—12 word pairs such as *warm-cool* or *lively-tedious* are chosen among 150 emotional words in Wei-ning et al. [2006]. People were asked to score 100 paintings along each word-pair on a $[-2, -1, 0, 1, 2]$ value scale. A principal component analysis is then applied to reduce the $12-$dimensional set to the three first factors accounting for 88% of the total variance. The authors shows that the first factor is well-described in images by color and luminance distributions for which they develop some fuzzy features. The second factor concerns some word-pairs that are well described by saturation and contrast information. The last factor deals with edge sharpness in images.

The photo-sharing website *Photo.net* gather millions of photos which are peer-rated along two qualities: *aesthetics* and *originality*. Datta et al. [2006] used a sample of this website made of artistic photos, and show first the correlation between these two qualities. Then they study 56 different chosen features which cover well-know aesthetics effects (colors, composition rules, depth of field,...). Using a support vector machine, they show that many computational features are indeed well correlated with the aesthetics ratings. Datta et al. launched an online visual search engine based on these results called *Acquine* [Datta et al. 2009].

This kind of deterministic approach does not support the ambiguity that often exists in both artworks content and user retrieval queries. Therefore Li et al. [2007] proposed to use fuzzy emotional descriptions using linguistic variables [Zadeh 1975] and some of the primary emotions proposed by Colombo [1999]. Semantic rules that maps the computational features with primary emotions are learned using a neural network. This approach allows description based on combined semantics among linguistic variables such as *very action and few uneasiness*.

A related perspective of application concern designers. Designers have to consider the aesthetic aspects of objects and images when conceiving new concepts. They often draw their inspiration from browsing large scale images databases online or in magazines. Novel visual processes for design engineers are investigated from this point of view and integrate affective computing concerns [Bouchard et al. 2008; Kim et al. 2008].

3.3 Technical abstraction

The literature dealing with technical abstraction can be organised in two categories. First, artwork authentication has been a major concern in art analysis. It can be seen as a technical abstraction in that it infers an information about who technically did the artwork. This task is a kind of boolean classification: the artwork is true or fake. It concerns forensic problems but also the simple assignment of an artwork to an artist. This latter issue appears when some masters used to lead an artist's workshop. Secondly, we group numerous studies that focus on artistic praxis such as characterizing the tools that have been used during the creative process. Let notice that we do not cover in this paper works dealing with digital image forgeries or watermarking techniques, the reader can find a recent introduction to this literature in Farid [2009].

Artwork authentication: One of the first methodology that has been proposed by Taylor et al. [1999] has been quite controversial [Jones-Smith and Mathur 2006; Taylor et al. 2006]. This approach based on fractal theory claimed to be able to authenticate Jackson Pollock paintings. This early study has been invalidated by Mureika et al. [2004], and then answered again by Taylor [2007]. The lack of comparison with a large ground truth is here anew a common drawback of most of the proposed methods. Another approach intends to authenticate Delacroix drawings based on ratios of binarized pixels among subparts of the image, and orientations histograms [Kroner and Lattner 1998]. The method is evaluated on a 60 drawings dataset containing 41 drawings made by Delacroix, and 19 drawings from other artists. Similarly, Lyu et al. [2004] showed preliminary results on an art authentication method applied to Peter Bruegel the elder and based on wavelets features. Let notice that although, or seeing that, these issues are of high importance for the art market, automatic approaches to support or stand for the expert have been seldom well received by professionals.

The Van Gogh and Krüller-Müller Museums made a dataset of a hundred high-resolution scans of Van Gogh paintings available to a group of computer vision researchers [Group 2009] dedicated to artist identification, also called *stylometry*. Their studies relies on wavelets decomposition filters and machine learning techniques [Johnson Jr et al. 2008; Jafarpour et al. 2009] and brush stroke textons [van der Maaten and Postma 2009]. This interesting latter study models local texture as a superposition of building blocks of textures (*textons*) picked out from a codebook [Varma and Zisserman 2003], thus avoiding any smoothing step usually involved in decomposition filters such as Gabor or Wavelets filters.

Artistic praxis studies. Stork [2009] wrote an introduction to the literature in this domain. Stork has led a long list of studies that address questions of artistic praxis such as perspective rendering and the putative use of optical systems by Renaissance artists (see Section 2.5). His approaches use semi-automatic techniques as tools to quantify, visualize or render observations on artistic questions. See Section 2.6 for methods to study artistic praxis used to render contextual information such as illumination.

Kammerer et al. published a series of papers on the identification of drawings tools based on their texture, using visible light [2003; 2004; 2007] or infrared light [2003; 2005]. The authors use a Canny-Deriche stroke detector combined with active contours. Vill and Sablatnig [2008] focuses on the stroke ending in order to achieve the identification. Again, these approaches intend to assist the art expert in analyzing some technical aspects of the artwork. Paintings cracks detection have also been investigated. This detection allows virtual restoration [Giakoumis et al. 2006; Gupta et al. 2008] and cracks classification [Abas and Martinez 2003]. Cracks in these papers are extracted using a thresholded morphological top-hat operator.

Hedges [2008] exploits the printed visible cues of weakening copperplates to order and date several editions made from one single plate. Lines indeed become thinner while editions are repeated due to erosion. Jafarpour et al. [2009] tackles the dating issue of Van Gogh's painting using wavelets and machine learning with a moderate success.

A part of the literature concerns color pigment studies. Many of them use some high resolution images [Martinez and Goodall 2008], sometimes being multispectral [Hiroshi et al. 2006; Mazzeo et al. 2007]. Here the technical problem can be digital color restoration [Pappas and Pitas 2000] or pigment identification [Kokla et al. 2008]. More works implies some multidisciplinary fields such as physic and chemistry. The core of these methods does not rely on image analysis tools and are thus not presented here.

To conclude, automatic approaches applied to artwork authentication has been first badly perceived by art experts. Care must be taken to ensure that these techniques are aimed to only support these experts in their tasks. Add to the fact that authentication is one of the most difficult problem, this application seems to have limited short-term perspectives. On the contrary, applications related to technical characteristics seem to have great potential. The recent profusion of papers shows that this domain is active. Museums' and curators' concerns combined to the size of nowadays digitized collections open numerous perspectives and issues that can be investigated by automatic analysis: pigments, cracks, preliminary sketches in underlying layers, pentimenti, engraving tools... These aspects can be analysed using different imaging techniques such as X-rays, UV and infrared imaging. As any conservative institutions, museums and curators first showed little motivation to encourage these kind of techniques, but it seems that this situation is reaching its tipping point.

4. RELATED RESEARCH TOPICS

This section extends several discussions initiated in Section 2. We believe that automatic artwork analysis can greatly benefit from broadening its source of inspiration. Manual analysis of artworks images is a topic of interest for several art-related professions: art historians, curators, visual semiologists, perception scientists, etc.

If we look at art history, an artwork can first be analyzed using an iconographical approach. It consists in studying the semantic content of an image, and to detect the visual stereotypes allowing to identify a subject, beyond its aesthetic value [Gombrich 1966]. As long as computational methods do not succeed in extracting the representational content in, at least, realistic images, then artworks cannot be reasonably analyzed using an iconographical approach. We recall that the semantic gap [Lew et al. 2006] is very large in visual arts images since artworks are often not perfectly realistic and the depicted reality of artists is highly variable.

Non iconographical approaches try to depict artworks along several other levels. For instance by analyzing factual characteristics [Kirsh and Levenson 2000]: artist's name, used medium, date of creation, artwork's title, etc. More subjective or uncertain levels can be found: represented subject category (e.g. portrait, still life), style. Finally, more formal description levels such as color composition, illumination, or contrast level can also be used [Barnet 1985; Sayre 1989; Carr and Leonard 1992]. These approaches shares a very common low-level vocabulary with the computer vision community. The different categories are not clearly identified or independent. An artistic style can be based on color or contrast information (e.g. chiaroscuro). The medium that has been used also influences formal features. However we see that art historians, and of course artists, has long been comfortable with formal description levels. This fact offered many easy starting points to conceive some artworks analysis methods which sound natural to both side of the research community. These starting points have been used as presented in the first part of this paper.

Visual pieces of arts are different from natural or medical images for instance in that they are created by a cognitive process. It can therefore be instructive not to only understand the way we look at an artistic image, but also to understand how a human being creates and structures his artwork. We tackle that question in Section 4.1. In Section 4.2, we discuss several studies that deal with visual perception from the artwork perception perspective. Expressive rendering is a computer graphics area that tackles many common issues with artworks analysis. We expose these common aspects in Section 4.3.

4.1 Cognitive process of an artist

Understanding and integrating how a human being creates and structures his artwork has often been bypassed in most of the previous works presented in Section 2. One of the first perceptual psychologist to have studied the cognitive process of artists is Arnheim [1954] in his seminal book. He formalized several high level concepts such as visual balance, shape, image space, light, color and movement that artists use. For each of these concepts, several tools are available to the artist [Arnheim 1969]. Arnheim support his claims by also studying some children drawings and their evolution during the childhood. This approach stresses how anybody integrate several depiction rules and tools to represent reality.

Procedural model. The same approach were used later by Willats [1997]. In his inspiring study, Willats proposed several depiction systems that let describe the artistic rules chosen by an artist. For instance, spatial systems map spatial relations in the scene into corresponding spatial relations on the picture, i.e. the projection rules and the perspective system chosen by the artist. Denotation systems map scene primitives into corresponding picture primitives. Primitives are atomic building blocks available to the artist. They can be zero-, one- or two-dimensional. Pointillism, for instance, is a good example of artwork only made of zero-dimensional primitives (dots). The attribute system corresponds to the features of each primitives (color, intensity, etc.). Willats and Durand [2005] later introduced a fourth system, called mark system. Marks complete the Willats framework with the physical texture layer attached to the primitives in drawings. It corresponds to the chosen combination of a physical tool and a drawing surface.

Artists facing the mirror. Artists themselves sometimes tried to understand and formalize their cognitive process. Klee [1966; 2004], Moholy-Nagy [1955] and Kandinsky [1979][Poling 1986] were professors at the Bauhaus school and taught some courses on artworks structures, color mechanisms, line-drawings perceptual issues, etc. Their books and theories are often quite complex and entangled but give evidences and intuitions on how these artists structured their creative process. An interesting common point of these studies is how they emphasize the expressive importance of lines. Another fascinating piece of work is the live documentary made by Clouzot [1954], filming Picasso behind his canvas. This film shows how Picasso structures the pictorial space, deletes or covers his works with numerous layers, looking for his inspiration. It also demonstrates a kind of hierarchical approach, going from first big scales of linear patterns to finer details, textures and surfaces.

Perception issues. Cavanagh et al. led numerous perception studies using artworks to stress specificities in the artist's and spectator's cognitive process. Cavanagh observed that artists use a restricted, or sometimes different, set of physical laws to represent a scene. Cast shadows [Cavanagh 2005], highlights [Cavanagh 1999] and reflections [Cavanagh et al. 2008] are three examples. Yet, this simpler set of rules does not perturb our visual process. We recognize objects in line-drawings for instance even when the same real objects does not handle any line (all human cultural societies and even monkeys handle this gift).

Neurophysiological issues. Livingstone [2008] in her introductory book studied the artistic process from a neuroscience point of view, more particularly based on luminance and color considerations. She distinguishes the *Where* and the *What* systems. The *Where* system is basically made of all the retinal rods that concentrates on the peripheral vision system. Rods are colorblind, fast, and highly contrast sensitive, and responsible for our perception of motion, space, position and depth. Illustrated by extensive real examples of paintings, she shows for instance how low luminance contrasts (equiluminant colors) both dispels the illusion of depth and infers jittering or motion effects. The *What* system is made of all the retinal cones, that concentrates on the central vision system. Cones are color selective, slow, insensitive to luminance contrasts and responsible of our ability to recognize objects, faces in complex detail. These two systems are not only distinguishable on the retina, but also at higher processing levels in the visual cortex.

Comics and sequential art. Comics are now unanimously considered as pieces of artwork. Will Eisner [2001] and Scott McCloud [1993] analyzed this art form in its specificities. Beyond what is common to non-sequential drawings, McCloud details the techniques that enable a cartoonist to infer rhythm effects and time flow, illusion of sound effects, and cultural symbols shortenings. He also proposes an interesting and general model of the visual content of an image. According to this model, any image can be placed in a weighted triangular scheme where corners are: realism level, pictorial-abstract level, and syntactic level. Along the realism-to-syntaxic axe for instance, a portrait will goes from as realistic as a photo to slightly stylized, greatly stylized (like a smiley icon), and finally the word "face". Similarly, along the realism-to-pictorial axe, a portrait would goes from realistic to more and more abstract (e.g. Cubists portraits). This model shares similarities with the model discussed in Section 3.1 and also used in [Hurtut et al. 2008], where the image in decomposed in a representational content (pure semantic) and the pictorial content (which includes the stylistic content). Still dealing with cartoon images and although its main concern is animation, the masterpiece of Williams [2001] contains many reading keys on how cartoonists draws and represent objects.

4.2 Cognitive process of a viewer

Works of visual art are quite distinct from natural images in that they are often stylized. This distinction influences the understanding of the scene through possible ambiguities as well as the visual effect delivered to an observer. What happens in our mind when we look at an image or a scene ?

Low-level visual reconstruction. How does our visual system reconstruct the visual scene, allowing us to recognize the objects ? The Gestalt school of psychology tried to answer this question at the low-level cognitive layer. Started in 1912 and until around 1970, this group produced a set of *Gestalt laws* that model how our perception gathers visual atomic components into more structured patterns from the first raw layer of our retina [Köhler 1967; Kanizsa 1979]. Among this set of rules, let cite: proximity, similarity, connectedness, continuity, symmetry, closure, relative size.

This reconstruction of the content of the images projected in our eyes also happens when we look at an artwork. Our mind will quickly try to recognize any known objects or scenes that could be represented in the artwork we are looking at and if it fails to do so, we will conclude that we are looking at an abstract artwork. Yet, when we look at an abstract artwork made of linear strokes for instance or any other geometrical components, we will reconstruct each of these components... as soon as it bears any meaningful structure. This leads to a known perceptual principle, sometimes called the Helmholtz principle, saying that we see a geometrical event as soon as this event is unlikely in a noisy situation. That is to say that the only type of image in which we do not *see* anything are white noise images. Gestalt laws and the Helmholtz principle have long remained without any mathematical formulation that could allow computer vision methodologies. The seminal work of Marr [1982] for instance relies on a neurophysiological approach. Yet, some recent methods tried to build on the Gestalt laws. Desolneux et al. [2008] proposed several methods to answers vision problems such as alignment detection, contours detection, vanishing point extraction, shape matching etc.

Important visual cues. Once this reconstruction process is admitted, another question that arises is: what are the visual cues that are really important in the recognition process of the objective content. Attneave [1954] and many others studies afterwards tried to answer this difficult question when dealing with a geometrical shape. Curvature extrema, inflexion points, corners relative surfaces are among the geometrical cues that were investigated (see e.g. [Winter et al. 2002]). The same question occurs about the visual cues that are important to the unconscious effect related to the subjective content. This aspect can be crucial in artwork analysis. The subjective content of an artwork is closely related to the aesthetic content and is thus of primary concern. Leyton [2006] proposed to use curvature extrema as the basic components of the subjective visual impact of geometrical shapes in artworks. This approach is closely related to Attneave work. It is not clear how the cues for objective and subjective content are related. This points out again how these two content are entangled. Julesz [1986] was one of the first to study the so-called preattentive local features that affect our visual process with distributions of small linear patterns. See Healey's thesis [1996] or webpage [Healey 2009] to have a good overview of all the preattentive features and processes that occurs prior to conscious attention.

Visualization and 3D reconstruction. In Bertin [1983] masterwork, *Semiology of Graphics*, the first theoretical foundation to Information Visualization is proposed. Following this seminal work, Ware [2004] regroups and discusses a large amount of studies on perception from a visualization point of view, hence often considering non-realistic images. He points out many perception features that can be either deliberately used by artists or which are at stake when we look at artworks: color and luminance constancy and contrasts, edge enhancements, preattentive features of shapes, color and spatial positions, texture contrast effects, perception of transparency etc. It is remarkable that many abstract expressionism paintings such as Barnett Newman's or Claude Tousignant's artworks induces very similar perceptual experiments as the usual visual illusions that are often encountered in perception books. Ware also addresses the perception step following the preattentive processing at the point where the image becomes thought. It is shown that this object *recognition* step is strongly view-point dependent. Besides, our brain reconstructs 3D structural model of objects during this task. Orientation and silhouette information are thus of major concern to help this mental reconstruction. Space perception issues are also discussed. To pursue the discussion made in Section 2.5, among depth cues that concerns pictorial images (monocular), let cite linear perspective, texture and size gradient, occlusions, depth of focus, cast shadows and shape-from-shading, repetitive patterns, aerial perspective due to atmosphere effects (see also Livingstone and Hubel [2008]). All these cues, principles and effects are routinely used in artworks and thus should be taken into consideration in analysis methodologies.

Eye-movements. Solso [1996] also explores and details cognition mechanisms, yet from the straightforward artwork point of view using extensive examples from art history. An interesting chapter deals with eye movements. Eye-movements of a spectator can be recorded using an eye-tracker for instance. Spatial measures show that it depends on the spectator intention if any, skills and artwork's style. Visual exploration can be *diversive* or *specific*. Diversive exploration can be thought of a quick wandering of the eyes with less than $300ms$ fixations. Specific exploration occurs when the viewer consciously or unconsciously seeks out specific information, usually with more than $400ms$ fixations. Livingstone [2008] also investigates eye movements when we look at artworks.

4.3 Expressive rendering

An active research subject in computer graphics is interested in proposing techniques to render some non-photorealistic images. This research domain is called non-photorealistic rendering (NPR) or also *expressive rendering*. A good introduction to this domain can be found in [Gooch and Gooch 2001]. At the origins of NPR, the *realistic* rendering of different typical artistic styles was the main goal, e.g. a method to automatically render an impressionist painting from a real photograph [Lee et al. 2007]. Therefore many techniques first used some physical models to reproduce the appearance of a specific medium combined with data driven constraints. See [Ostromoukhov 2002; Reynolds 2003] for surveys on this type of approach. This scope rapidly led the domain to the following conclusion: the more we understand the creative and cognitive process of an artist and a spectator, the better is the illusion of a man-made painting. Nowadays, NPR broadened its scope and inspiration. The field found many other interesting applications beyond the scope of reproducing a specific style. The use of NPR techniques can offer new creative tools to computer graphic users expanding their possibilities or alleviate their workload. Artworks, drawings, sketches are also known to be excellent communicative tools. Integrating automatic artistic techniques inherited from the artist knowledge and visual principles accumulated for centuries, can also be brought to every user that have to produce an efficient communicative image, video or presentation, or any image manipulation for instance. This intent is shared by Bertin and Ware studies that we presented in last section.

The need for image analysis techniques is explicit in several papers [Jodoin et al. 2002; Barla et al. 2005; Grabli et al. 2004] and also in the research statement of research group at INRIA in France [IMAG 2003]. NPR scientists also clearly observed that visual perception principles might be one of the keystones of all their issues. Healey is one the many scientists that stands at the junction between perception, visualization and NPR, see for instance [Healey 2001]. See also recent works from Benard et al. [2009] on texture perception, Cole et al. [2008] on line-drawings. NPR advances can be found in major computer graphics proceedings such as SIGGRAPH or Eurographics where specific sessions are regularly dedicated to NPR, or also in devoted conferences or symposium such as NPAR and *Computational Aesthetics*. NPR papers are naturally oriented towards computer graphics applications and may not always include or be directly transposed to artwork analysis problems. Yet we cite this domain because it could be a source of inspiration on the scientific bolts that still occupy both communities.

5. CONCLUSION

In this paper, a detailed survey of the literature of 2D artworks analysis techniques is presented. This survey is structured in two main parts, along the semantic stairways and the abstraction categories. Finally, the discussion is opened with works from related fields such as artist's and viewer's cognition processes and expressive image rendering.

To conclude, we believe that the following issues and challenges are of particular importance to the artwork analysis community. (1) The integration of *a priori* knowledges based on the artist's and spectator's cognitive processes could be of great benefit for most applications and content categories. (2) Considering image retrieval applications, emotional abstraction, affective computing and all aspects that get in touch with the artistic uniqueness offer promising perspectives. (3) Evaluation in cultural heritage applications is tactful due to severe constraints on cultural institutions and copyrights. A major and crucial challenge is to gather copyright-free databases of images that could be collectively used to compare different methodologies. The recent example of the Van Gogh and Krüller-Müller Museums providing a high-quality database to a large group of scientists and the approaches that these latter proposed should encourage more cultural institutions to follow their footsteps. (4) The development of supporting tools for the technical analysis of artworks still hold a great potential that could interests and encourages cultural institutions and curator departments in particular. (5) As stressed by the DELOS-NSF working group, image retrieval applications also hold a formidable potential to improve accessibility to the worldwide cultural heritage for the hundred of millions of internet users. More intuitive interfaces and querying solutions systems should be developed.

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