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SEMANTIC AND ABSTRACTION CONTENT OF ART IMAGES

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Abstract

In this paper the semantic and abstraction content of art images is studied. Different techniques for search in art image repositories are analyzed and new ones are proposed. The content-based retrieval process integrates the search on different components, linked in XML structures. Some experiments over 200 paintings of six Israel contemporary artists are done and analyzed.

Keywords: High Level Semantic Retrieval, Art Painting Repositories, Content-based Image Retrieval

1 INTRODUCTION

Since its first edition in 1962 Janson's History of Art [Janson, 2004] is one of the most valuable sources of information spanning the spectrum of Western art history from the Stone Age to the 20th century. It became prominent introduction to art for kids and a reference tool for adults trying to remember the identity of some embarrassingly obvious image. The colorful design and vast array of extraordinarily produced illustrations gives not only receiving of dry information, but also deep emotion fulfilling by touching of masterpieces. But now online search engines have whetted web surfers' appetites for context and information. There are a host of digital databases offering easily accessible touch to digital items and presenting the colorfulness of art history. The used metadata give all additional information from pure technical details, connected with the way of creating the artifacts, to deep personal details from the life of the creators. This helps the observers to better understand input message in the masterpieces.

In the field of image retrieval we have faced with obvious difference between human vision system, which has evolved genetically over many millenniums, and computer possibilities, which is limited to processes of capturing and analyzing pixels. Even in this first step of image recognition we have a hard task to find appropriate machine algorithms to represent the picture, which are different of human ways of perceiving, but which can give similar results for interpreting the aesthetic and semantic content in the pictures. Naturally, the interpretation of what we see is hard to characterize, and even harder to teach a machine. Over the past decade, ambitious attempts have been made to make computers learn to understand, index and annotate pictures representing a wide range of concepts.

The unique specific of visual pieces of arts is that they are created by a cognitive process. It can therefore be instructive not only understand the way we look at an artistic image, but also to understand how a human being creates and structures his artwork. Each touch to the artwork causes building the bridge between cultures and times. As was mentioned in [Chen et al, 2005] "research on significant cultural and historical materials is important not only for preserving them but for preserving an interest in and respect for them".

The rest of the paper is organized in the following way. Section 2 gives a brief overview of main directions of presentation and analysis of artworks. In section 3 an attempt for describing the taxonomy of art image content is proposed. Section 4 presents our approach for extracting attributes, concerning different aspects of image content in order to receive discriminating profiles for describing abstraction specifics of artists, schools or movements. Section 5 contains a description of program realization and conducted experiments over a dataset, which contains artworks of contemporary Israel artists. Finally some conclusions and future work directions are highlighted.

2 DIGITAL PRESENTATION AND ANALYSIS OF ARTWORKS

Handling with digital copies of artworks has a wide spectrum of different directions and concern different types of users:

- museum workers: Analysis of the artwork itself, its lifecycle, preservation and restoration are very important but heavy tasks where automatic image processing techniques have proved their usability during last decades;
- universal citizens: Taking into account that artwork brings a specific authors' message to the viewer the computer should provide the ability to present history, context, and relevance in order to enrich education, enhance cross-cultural understanding, and sustain one's heritage and cultural diversity;
- computer scientists: Except wide standard questions for serving the processes of image analysis and managing repositories, the grand challenge is determining image semantics and automatically verbalizing it.

2.1 Automatic artwork analysis techniques

In spite of the fact that computer still not wield the human vocabulary and semantic, its methods and abilities for analysis information already make him irreplaceable assistant in many fields of study of art. Computers can analyze certain aspects of perspective, lighting, color, the subtleties of the shapes of brush strokes better than even a trained art scholar, artist, or expert. As David Stork has mentioned [Stork, 2008] "the source of the power of these computer methods arises from the following:

- the computer methods can rely on visual features that are hard to determine by eye, for instance subtle relationships among the structure of a brush stroke at different scales or colors;
- the computer methods can abstract information from lots of visual evidence;
- computer methods are objective, which need not mean they are superior to subjective methods, but promise to extend the language of to include terms that are not highly ambiguous."

In the last years several efforts have been devoted to the application of image processing and digital imaging techniques in order to facilitate museums activities. Many successful projects in these directions were funded by Esprit, Impact, Raphael, and IST programs. They provide the most conventional image processing for the museum, such as geometric correction, registration, mosaicing, etc. [Maitre et al, 2001]. Numerous applications have to consider fully or partially some artworks analysis techniques: e.g. image enhancement for publication purposes, virtual restoration of artworks (inpainting, fading color enhancement, crack removal, etc.), image-based 3D reconstruction (sculptures, archaeological sites, etc.), artistic practices studies (color palette statistics, creative process, dating, etc.), art history investigation, authentication, watermarking, expressive rendering, etc. [Hurtut, 2010].

2.2 Image repositories

In 2004 David Mattison, named as master of the online archive universe, publish series of lectures in Searcher magazine focusing on state-of-the-art of available Web resources and image databases, current techniques for image retrieval, and finishing with mentioning of national collections that document the art history of Western civilization from medieval times through the 19th century [Mattison, 2004]. The creators of this wealth of image databases, art collections and guides usually are academic, librarian, commercial, and private art museums and galleries, amateur and professional art historians, artist sites, commercial image agencies, auction houses (usually on a temporary basis), etc.

Convenient image capture techniques, inexpensive storage, and widely available dissemination methods have made digital images a suitable and easily available information format. This increased availability of images is accompanied by a need for solutions to the problems in indexing and retrieval. Traditional concept-based indexing uses controlled vocabulary or natural language to express what an image is or what it is about. Newly developed content-based techniques rely on a pixel-level interpretation of the data content of the image. The upper stage of indexing techniques – concept-based indexing is based on mixing of simple text-based and content-based tools, taking into account the additional information for interconnections between perceived information from the main player of this process – "the user".

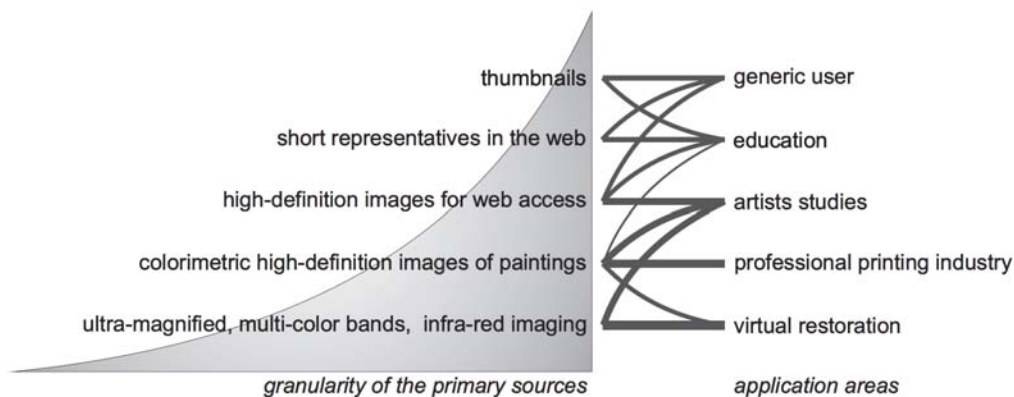


Figure 1. Sensitive representation of digitalized artworks in relation with their usage

The granularity of used digitalized sources of artworks is in accordance with their usage. Figure 1 simply represents connections between different kinds of users and the amount and quality of corresponded digital sources. Usually for professional analysis in museums special kinds of images, received from different photographic processes such as multi-color banding, x-rays and infra-red imaging is used. For the purposes of professional printing industry very high definition and quality images are produced. But, royalty and copyright restrictions from one side [Mattison, 2004], the necessity of high speed receiving via Internet from the other side, and the limitations of visual devices (monitors) from the third side, impose the restriction of the amounts of digital images. Usually in the Internet space the presentations of the art paintings vary from about 100 pixels for front presentation of the paintings (as thumbnails), thorough middle presentations designed for presenting the painting on the screen usually with additional text information, concerning the certain picture (author, sizes, techniques, locality, history of the creation, subject comment, etc.), and finally up to 4000 pixels (often watermarked items).

2.3 Intelligent search

In the image retrieval systems, an important parameter to measure user-system interaction level is the complexity of queries supported by the system. The queries can use different modalities, such as: direct filling the values of the desired features; giving the image or sketch as example; keywords or free-text, and their combination. Exploring user needs and behaviors is a basic and important phase of

system development. Relevance feedback is very important step in image retrieval, because it defines the goals and the means to achieve them. It became a natural bridge to the next phase in web development to Web 3.0 "the portable personal web" [Agarwal, 2009], where the adaptation to user specifics and aptitudes will be based on capturing the historical information thorough searching the Web.

3 TAXONOMY OF ART IMAGE CONTENT

Johannes Itten [Itten, 1961] has given very good formulation of messages that one artwork sends to the viewer. He points three basic directions of evincing color aesthetics:

- Impression (visually);
- Expression (emotionally);
- Construction (symbolically).

These characteristics are mutually connected and can not live of full value alone: symbolism without visual accuracy and without emotional force would be mere anemic formalism; visually impressive effect without symbolic verity and emotional power would be banal imitative naturalism; emotional effect without constructive symbolic content or visual strength would be limited to the plane of sentimental expression. Each artist works according to his temperament, and must emphasize one or another of these aspects [Itten, 1961].

Different styles in art paintings are connected with used techniques from one side and aesthetic expression of the artist from other side. The process of forming artist style is very complicated process, where current fashion painting styles, social background and personal character of the artist play significant role. All these factors lead to forming some common trends in art movements and some specific features, which distinguish one movement to another, one artist style to another, one artist period to another, etc. From other side the theme of the paintings also stamp specifics and can be taken into account. The compositions in different types of images (portraits, landscapes, town views, mythological and religious scenes, or everyday scenes) also stamps some rules, aesthetically imposed for some period.

When humans interpret images, they analyze image content. Computers are able to extract low level image features like color distribution, shapes and texture. Humans, on the other hand, have abilities that go beyond those of computers. The humans draw own subjective conclusions. They place emphasis on different parts of images, identify objects and scenes stamping their subjective vision and experience. The emotion that one person gets from seeing in an image, and therefore associates with it, may differ from another person's point of view.

Trying to put some basis for bridging the gaps between receiving the information from human and from computers [Burford et al, 2003] suggest taxonomy of image content as extracted by the viewer of an image. In his brilliant survey for 2D artistic images analysis Tomas Hurtut [Hurtut, 2010] gives profiling of extraction primitives and concepts accounting the specific of artworks. He split image categories into three groups: image space, semantic space and abstract space. Image space contains visual primitives, needed to record an image through visual perception. Semantic space is related to the meaning of the elements, their potential for semantic interpretation. Finally abstract aspects that are specific to art images and reflect cultural influences, specific techniques as well as emotional responses evoked by an image form the abstract space.

In Figure 2 we give our vision for classifying feature concepts (a slightly differ from Hurtuts' proposition) with pointing examples of used techniques for extracting visual primitives as well as some of closer relationships between concepts from defined spaces. All concepts are mutually connected – for instance emotional abstractions depends on specific expressive power of the artists (which is closely connected with visual perception primitives), thematic of the painting (concerning objective semantics of the paintings) as well as with the viewpoint of observer with his cultural and psychological peculiarities.

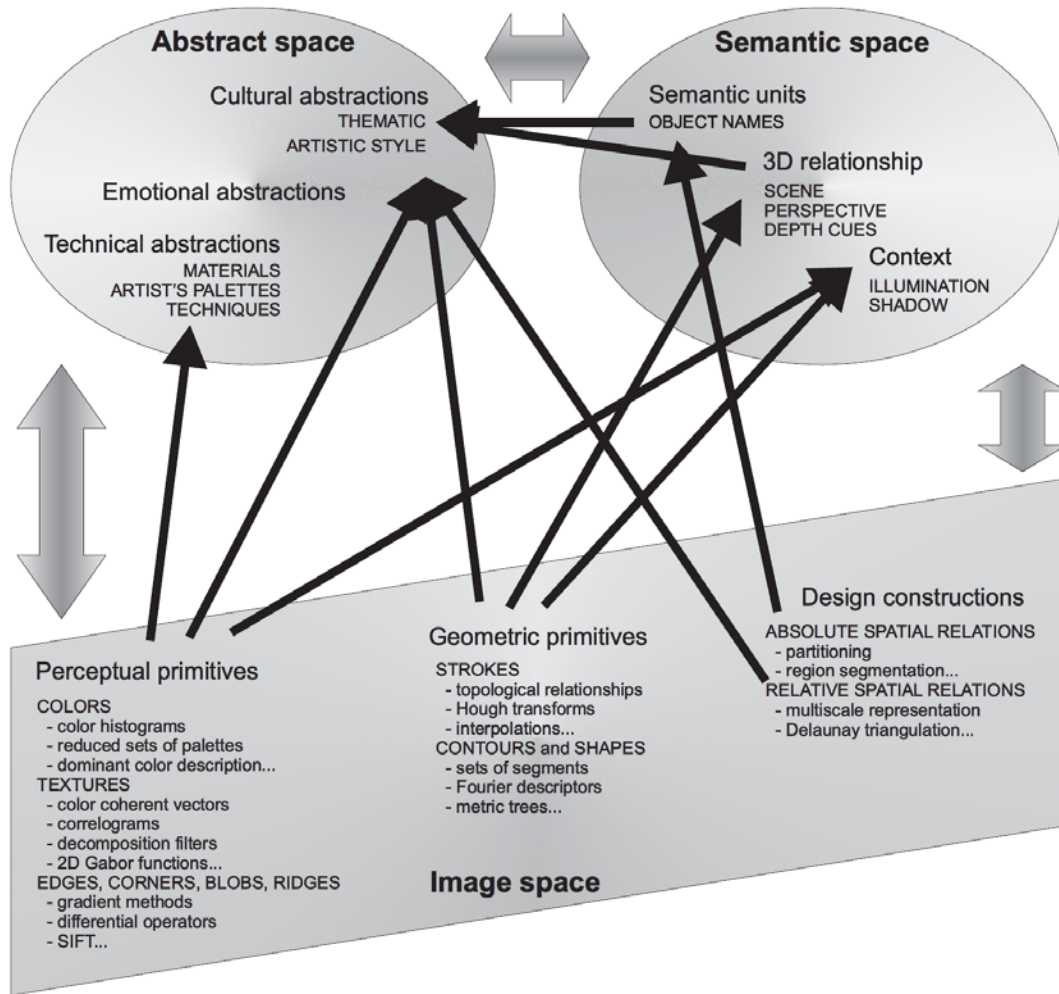


Figure 2. A taxonomy of image content, inspired from [Burford et al., 2003] and [Hurtut, 2010]

Resolving these questions come up against the problem that in real-world contexts, it is in fact dynamic in nature. The information that one can extract from the visual data for a one-time trained image recognition model does not change, but on the other hand, the interpretation that the same data have for a user in a given situation changes across users as well as situations.

4 PROPOSED ATTRIBUTES FOR ARTWORK ANALYSIS

There is evidence that different image features work with different levels of effectiveness depending on the characteristics of the specific image data set. Horst Eidenberger [Eidenberger, 2003] analyses descriptions based on MPEG-7 image features from the statistical point of view on three image data sets. For example, he found that Color Layout, like Color Structure, perform badly on monochrome images, that Dominant Color performs equally well on the three data sets, etc. This study demonstrates that, even if it is not possible, in general, to overcome the semantic gap in image retrieval by feature similarity, it is still possible to increase the retrieval effectiveness by a proper choice of the image features, among those in the MPEG-7 standard, depending on the characteristics of the various image data sets. Obviously, more homogeneous the data set is, better results can be obtained.

The goal of our research was to examine different extracted attributes, which represent global or local information for the images from one side and various cues of color and texture distribution within the images from other side.

We analyze visual features, based on the MPEG-7 descriptors, which capture some significant specifics of image colorfulness and texture [ISO/IEC 15938-3] as well as the information gathered by representing of the pixels in HSL color space. Especially for extracting color harmonies and contrasts RYB color space is used, because artists' definition of complimentary colors is based on it.

4.1 Global attributes

The global features represent mean color information about image. The pixels from each image (with dimensions $m \times n$) are transformed from RGB to HSL color space, producing two-dimensional matrices for Hue (I_H), Saturation (I_S) and Luminance (I_L). This conversion is prompted by the fact that in color psychology color tones, lightness and saturation play important roles, and hence working in the HSL color space, which is very near to human perceiving of the complex structure of the color, makes computation more convenient.

We use the average pixel value to characterize *mean hue* – $\frac{1}{m \times n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} I_H(i, j)$, *mean saturation* – $\frac{1}{m \times n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} I_S(i, j)$ and *mean luminance* – $\frac{1}{m \times n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} I_L(i, j)$.

Influencing of already extracted common rules for quality in photograph art [Datta et al, 2006] we use some similar attributes, focusing on the center of the images. We examine proposition for "the rule of thirds" (which is a sloppy approximation to the "golden ratio") and use similar attributes with described in [Datta et al, 2006] for the center rectangle when the image is split into 3×3 equal tiles but

using HSL color representation: *mean hue (center)* – $\frac{9}{m \times n} \sum_{i=m/3}^{2^*m/3} \sum_{j=n/3}^{2^*n/3} I_H(i, j)$, *mean saturation (center)* – $\left(\frac{9}{m \times n} \sum_{i=m/3}^{2^*m/3} \sum_{j=n/3}^{2^*n/3} I_S(i, j)\right)$ and *mean luminance (center)* – $\left(\frac{9}{m \times n} \sum_{i=m/3}^{2^*m/3} \sum_{j=n/3}^{2^*n/3} I_L(i, j)\right)$.

Looking to *aspect ratio*, defined as m/n a generalized feature *aspect*, which takes values "P" (if $n > m$) or "L" (if $m > n$) is examined.

Another examined feature is *gradient*, which is calculated as average value of color gradation in the

image $\frac{1}{(m-1) \times (n-1)} \sum_{i=1}^{m-2} \sum_{j=1}^{n-2} G(i, j)$, where $G(i, j) = \sqrt{(I_L(i, j) - I_L(i-1, j+1))^2 + (I_L(i, j) - I_L(i+1, j-1))^2}$

(for lighting the computations we use only diagonal differences).

4.2 Attributes based on color harmony and contrast

Second group of features contains characteristics, which extraction algorithms are described in [Ivanova and Stanchev, 2009]. Here we give a short explanation. The system transforms percentage values of dominant colors of the image into quantized RYB color space. Quantization is made in accordance of Itten's theory [Itten, 1961]. As a result, every picture is represented with three arrays, containing percentage values of Hue (12 color bins and one for achromatic colors), Saturation (5 bins by default) and Luminance (5 bins by default). On the base of this information following attributes are examined:

- *Hue order vector* – contains number of dominant hues and positions of dominant hues, ordered in decreasing percentage. The number can vary from zero for achromatic paintings, to maximal defined dominant colors. When image is not achromatic this is the number of ordered hues, which sum of the percentages exceed some (expert-defined) value;
- *Hue harmony* – the values of the hue harmony depend from the number of dominant hues and can be *achromatic, analogous, complimentary, triads*, etc.;

- *Cold/warm contrast* – depends of proportion of families of colors p_{warm} , p_{cold} , and $p_{neutrals}$, which is calculate as sums of dominant colors belonging in corresponded regions of hue. The values are *warm*, *cold*, *neutral*, *warm-cold*, *warm-neutral*, *cold-neutral*, etc.;
- *Saturation order vector* – number of dominant saturations and theirs positions, ordered in decreasing percentage. The numbers of dominant saturations is equal to the number of ordered saturations, which sum of the percentages, exceed some given by expert value;
- *Saturation combinations* – depending of number of dominant saturations and theirs disposition, this attribute can receive values such as *monointense*, *contrary*; *smooth*, etc.;
- *Lightness order vector* – defined in the same manner as *Saturation order vector*;
- *Lightness combinations* – similar to *Saturation combinations*.

Figure 3 represents an example of received harmonies attributes for painting "Naples Red" of Nurit David.

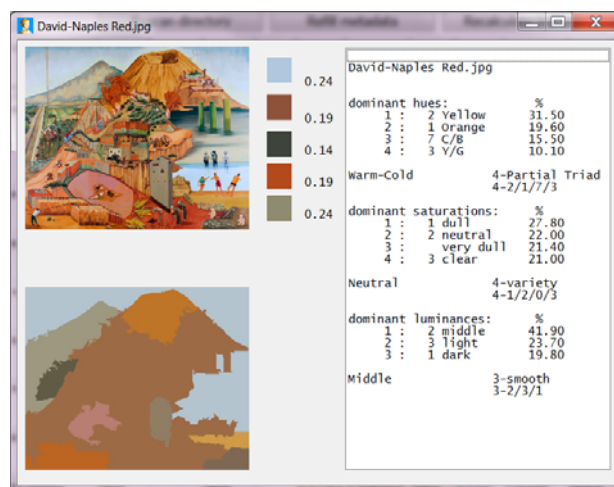


Figure 3. Harmonies attributes for Nurit David's artwork "Naples Red"

4.3 Attributes, capturing local information

Third part of features is based on vector quantization of MPEG-7 descriptors, calculated over tiles of the image. The proposed approach, represented in [Ivanova et al, 2010], consists of the following steps:

- (1) the images are tiled into $m \times n$ non-overlapping rectangles to capture more detailed information;
- (2) the tiles of the images are clustered for each MPEG-7 descriptor;
- (3) vector quantization is used to assign a unique value to each tile, which corresponds to the number of the cluster where the tile belongs to, in order to reduce the dimensionality of the data.

As a result of this step for each image we receive $x \times m \times n$ numerical attributes, where x is the number of used MPEG-7 descriptors. The system allows using only subset of the available tiles – chess order or left/right side. Analysis of the significance of received attributes [Ivanova et al, 2010] shows the possibility to use only left or right part of the image without essential losing of accuracy. Of course, each rule in the art is very relative. Modern art movements, which use abstract impressions based on asymmetrical color and/or design balance, can be recognized just by this inequality.

5 PROGRAM REALIZATION AND EXPERIMENTS

For obtaining the explained features special tools was realized in the laboratory for art-painting semantic image retrieval "Art Painting Image Color Aesthetic and Semantic" (APICAS). APICAS refers to Multimedia Content Management System MILOS [Amato et al, 2004] in order to receive MPEG-7 descriptors values. In APICAS special clustering algorithms, which taking into account specific similarity measures for MPEG-7 descriptors, are under development. For now, as a clustering algorithm the program "vcluster", which is part of the CLUTO open source software package [Karypis, 2003], is used. The examination of the accuracy for predicting the artists' names is made in the Waikato environment for Knowledge Analysis WEKA [Witten and Frank, 2005].

For showing functionality of the system we have used a dataset that includes 200 paintings of 6 Israel contemporary artists: Nurit David (30), Maurice Ganis (45), Moshe Gershuni (30), Moshe Kupferman (25), Raffi Lavie (30), David Reeb (40). In brackets the number of images is given. Part of images is given from Givon Art Gallery¹. Nurit David was also presented in the gallery of Mimmo Scognamiglio², Maurice Ganis made own presentation in Flickr³, part of paintings of Moshe Gershuni are from Sara Asperger Gallery⁴, Moshe Kupferman⁵ and David Reeb⁶ have own sites.

The attributes concerning vector quantization of MPEG-7 descriptors over tiles were made with 4x4 tiling, using 30 vector quantization values for each MPEG-7 descriptor. In Figure 4, the tiles, closest to centroids for Color Structure Descriptor, are presented.

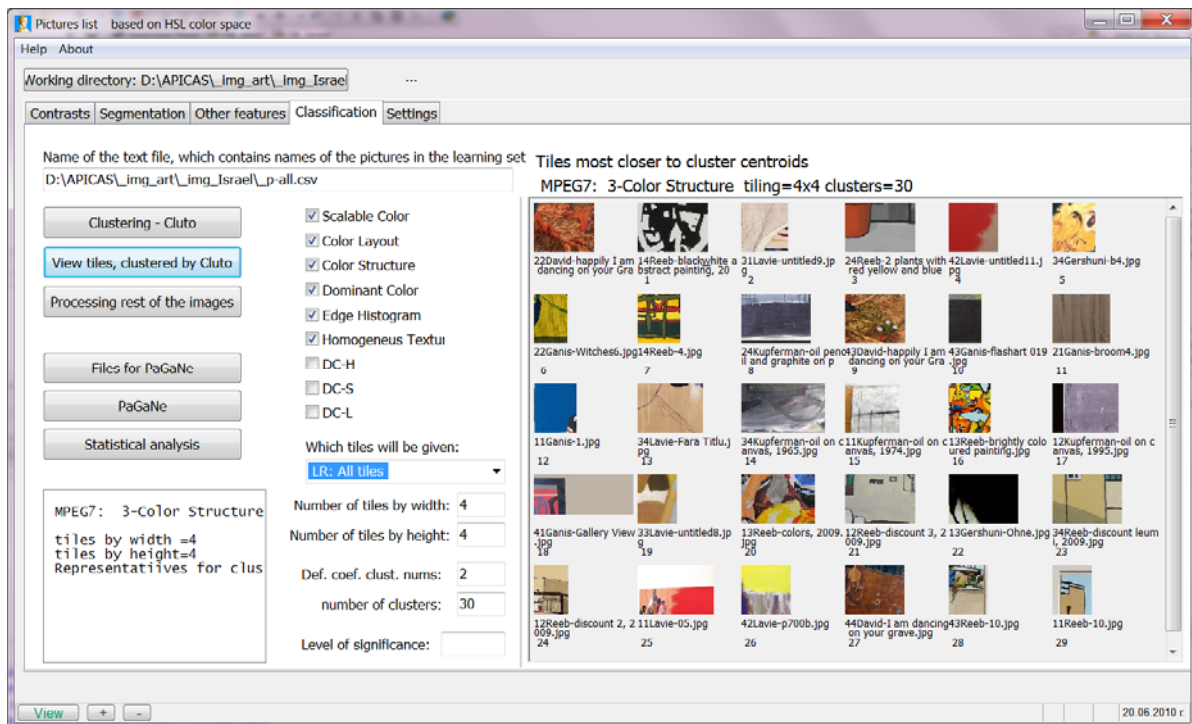


Figure 4. Representatives of cluster centroids for Color Structure Descriptor

¹ www.givonartgallery.com

² <http://www.mimmoscognamiglio.com/>

³ <http://www.flickr.com/photos/maurice-ganis/>

⁴ <http://www.sara-asperger-gallery.de>

⁵ <http://www.kupferman.co.il/>

⁶ www.davidreeb.com

We have examine datasets, which include different sets of described above attributes with the artists' names as class labels. Tests are provided using 10-fold cross-validation. As classification algorithm we have used BayesNet from WEKA, which shows best results from this family of classifiers for such datasets.

The experiments shows that using first and second types of attributes and local attributes based only on Color Structure and Edge Histogram descriptors are enough for receiving good classification accuracy (Figure 5).

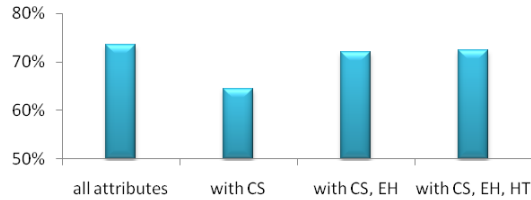


Figure 5. Classification accuracy giving from BayesNet using different sets of attributes

The explanation of this result hides in the fact that attributes based on color harmony and contrast make good presentation of color interconnections and thus Dominant Color descriptor gives not more quite valuable information. By its nature Color Structure descriptor capture information not only for the color presence but also for its disposition, because of this the corresponded attributes brings additional information for color interaction in the artists' style.

	David	Ganis	Gershuni	Kupferman	Lavie	Reeb	Sum by rows
David	24	0	4	0	2	0	30
Ganis	3	31	2	6	1	2	45
Gershuni	9	1	12	6	2	0	30
Kupferman	0	0	5	18	1	1	25
Lavie	3	0	1	0	26	0	30
Reeb	0	1	0	3	0	36	40
Sum by columns	39	33	24	33	32	39	200

Table 1. Confusion matrix of recognition results of ten-fold cross validation over given dataset

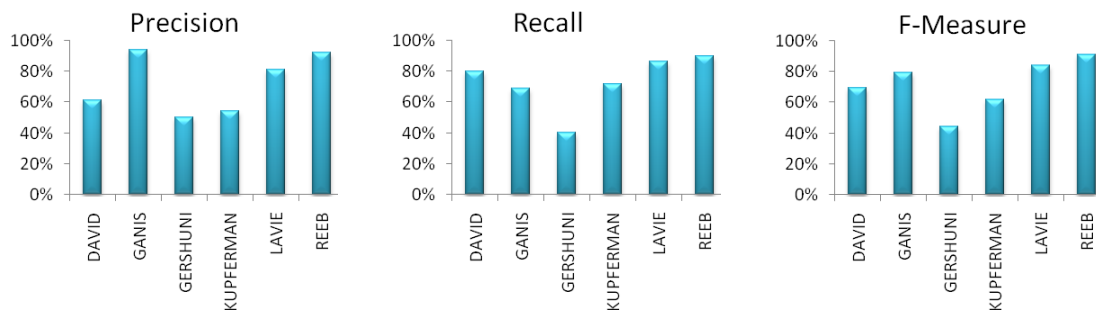


Figure 6. Precision, recall and F-Measure for observed class labels

Table 1 shows more detailed information about classification accuracy for given dataset. The rows indicate the class where the image actually belongs to. The columns show the class label assigned to the image by the classifier. The numbers of correctly recognized images of the corresponded class are represented on the diagonal. Based on this information, precision, recall and F-measure are shown in Figure 6.

As we can see mainly paintings from Kupferman are wrongly recognized as Gershuni's works, which can be easily explained by the fact that both of them have abstract paintings. The diversity of color palette as well as different techniques used in Gershuni paintings leads to decreasing of classification accuracy mainly from produced false-positives and false-negatives cases.

6 CONCLUSION

In this paper we present and analyse tools for indexing and searching in paintings repositories, according to visual characteristics of their content. We have tackled the non-trivial process of image crawling and descriptive feature extraction. The proposed methodology will help us in the transition from Web 2.0 to Web 3.0. Without a breakthrough technology, superior Web 3.0 tools will be more difficult to develop than their counterparts for Web 2.0. This will be part of creation of new tools which will offer society new greater sophistication, complexity, and functionality. XML-level are unaware of the new generation Semantic Web languages, such as RDF(S) and OWL. The integration of semantic understanding of pictures with personalized delivery implies new questions.

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