Automatic Tagging of Art Images with Color Harmonies and Contrasts Characteristics in Art Image Collections

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Abstract **– In this paper we present a classification of color harmonies and contrasts, which is consistent with human perceiving of visual expression. It is conformed to the possibilities of automatic extraction of visual information from digitalized copies of art images. The classification is done on the base of the three main characteristics of the color most closed to the human perception – hue, saturation and lightness. Functions for automatic features extraction from digital images are defined. These functions are realized as part of a virtual laboratory "Art Painting Image Color Aesthetic and Semantic" (APICAS). The system can be used by designers and art students for searching images, having certain harmonies or contrasts in image collections as well as a for examining specifics of artists or movements. In future we will use the system as a Web 2.0 service, which could be included in a virtual learning environment.**

Keywords – Content-Based Image Retrieval; Image content; Color; Harmonies; Contrasts

I. INTRODUCTION

One of the most felicitous analogies for presenting the existing semantic gap in area of Content-Based Image Retrieval (CBIR) can be found in "The Hitch-Hiker's Guide to Galaxy" by Douglas Adams. In this story, a group of hyper-intelligent pan-dimensional beings demand to learn the "Answer to Life, the Universe, and Everything" from the supercomputer Deep Thought, specially built for this purpose. It takes Deep Thought 7½ million years to compute and check the answer, which turns out to be "42" [2]. The efforts of covering the semantic gap in CBIR are turned to avoid these misunderstanding between human perceiving and the ways of communications and computer manner of low-level representations.

As it is mentioned in [3], the user questions in image search are partitioned into three main levels:

Low level – this level includes basic perceptual features of visual content (dominant colors, color distribution, texture pattern, etc.). Low-level queries and analysis can support the retrieval of art images in order to seek some specifics or common characteristics between artists, schools or movements.

Intermediate level – this level forms next step of extraction from visual content, connected with emotional perceiving of the images, which usually is difficult to express in rational and textual terms. The visual art is an area, where these features play significant role. Typical features in this level are color harmonies and contrasts, because one of the goals of the painting is to produce specific psychological effects in the observer, which are achieved with different arrangements of colors.

High level – this level includes queries according to rational criterions. In many cases the image itself does not contain information, which would be sufficient to extract some of the characteristics. For this reason current high-level semantic systems still use huge amount of manual annotation.

Different features' levels imply different ways for communication between the user and the CBIR system. When a system uses low-level properties such as color percentages, color layout, and textures (see the pioneer of the area QBIC, developed by IBM [4]), the queries do not need to be described in words. When working with such systems, the user can select a sample image and the system returns all images that are "similar" to it. For systems, which operate with high level features, only choosing a sample or drawing a sketch and search similar characteristics is not sufficient, even because such system has to "know" which of characteristics are targeted by the user. There are two mutually connected tasks in this area:

- Defining features and terms, which present certain effect or criterion and describing correlation between defined concepts;
- Finding appropriate algorithms for generating metadata, which alone or in combination with present terminal features and terms will allow improved image search as well as proposing adequate methods and tools for establishing belonging of a sample to same concept.

This paper presents an experimental software system for intermediate semantic image search based on color harmonies and contrasts. These ideas were firstly introduced in [1]. Section 2 stops the attention on the different sides of the image content. In Section 3 we make an analysis of the phenomenon of the impact of one color on the perception of others. In Section 4 we present a hierarchical classification of different types of harmonies and contrasts in order to be used as base for further analysis and extraction tools from image databases. In Section 5 we describe an experimental software system, which integrates the proposed tools. Section 6 contains experimental results made by the realized system. Finally, conclusion and future work are presented.

II. TAXONOMY OF ART IMAGE CONTENT

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. Numerous applications have to consider fully or partially some artworks analysis techniques: e.g., virtual restoration of artworks, artistic practices studies, art history investigation, authentication, watermarking, expressive rendering, etc. [5]. From point of view of universal citizen, 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.

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 that 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, with much progress.

The unique specific of visual pieces of arts is 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. Each touch to the artwork causes building the bridge between cultures and times. As was mentioned in [6] "research on significant cultural and historical materials is important not only for preserving them but for preserving an interest in and respect for them".

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 set some rules, aesthetically imposed for some period.

Trying to put some basis for bridging the gaps between interpreting the information from human and from computers several taxonomies of image content as extracted by the viewer of an image are suggested. Alejandro Jaimes and Shih-Fu Chang [7] are focused on two aspects of image content – the received visual *percepts* from the observed images and underlying abstract idea, which corresponds to *concepts*, connected with the image content. In his brilliant survey for 2D artistic images analysis Tomas Hurtut [5] expands taxonomy given by Bryan Burford, Pam Briggs and John Eakins [8]. He gives profiling of extraction primitives and concepts accounting the specific of artworks, splitting image categories into three groups: *image space*, *object space* and *abstract space*.

In our investigation we consent Hurtut's proposition with slightly changes of distribution of features in the groups. We examine *image space*, *semantic space* and *abstract space*. Image space contains visual primitives, needed to record an image through visual perception. Image space includes perceptual primitives (color, textures, local edges), geometric primitives (strokes, contours, shapes) and design constructions (spatial arrangement, composition). Semantic space is related to the meaning of the elements, their potential for semantic interpretation. Semantic space consists of semantic units (objects), 3D relationship between them (scene, perspective, depth cues) and context (illumination, shadow). Abstract aspects are specific to art images and reflect cultural influences, specific techniques as well as emotional responses evoked by an image.

Several big projects addressed the description of the high-level semantic and abstraction concepts in the art domain:

- *The Getty vocabulary databases* [9] are produced and maintained by the Getty Vocabulary Program. They contain terms, names, and other information about people, places, things, and concepts relating to art, architecture, and material culture. The vocabularies in this program are: The Art and Architecture Thesaurus (AAT), the Union List of Artist Names (ULAN), the Getty Thesaurus of Geographic Names (TGN), and finally the Cultural Objects Name Authority (CONA), which expects to be introduced in 2011;
- *WordNet* [10] is a large lexical database of English, developed under the direction of George A. Miller. WordNet is freely and publicly available for download. Although it is not domain-specific, it is a useful tool for computational linguistics and natural language processing especially for English-language texts;
- *Iconclass* [11] is a hierarchical system designed for art and iconography, developed by the Netherlands Institute for Art History. It includes the following main divisions: Abstract, Non-representational Art; Religion and Magic; Nature; Human being, Man in general; Society, Civilization, Culture; Abstract Ideas and Concepts; History; Bible; Literature; Classical Mythology and Ancient History.

In order to present properly concepts and their correlation between low and intermediate levels as well as the connections to the high level, every system usually creates its own dataset. This allows implementing the specific elements of the used methods and tools. Some examples are:

- The "Pictorial Portrait Database" [12] uses a hierarchical database indexing method based on Principal Component Analysis. Its description model is based on the eyes as the most salient region in the portraits;
- An approach for extraction of low level color characteristics and their conversion into high level semantic features using Johannes Itten theory of color, Dempster-Shafer theory of evidence and fuzzy production rules is suggested in [13];
- Hering theory of complementary colors is in the ground of the approach for extracting high level concepts, proposed by [14];
- The team, headed by R. Jain uses annotation of paintings based on brushwork, where brushwork is modeled as part of the annotation of high-level artistic concepts such as the artist name using low-level texture [15].

III. Human Perception of the Color

From all the senses that connect us to the world – vision, hearing, taste, smell, and touch – vision is the most important. More than 80% of our sensory experiences are visual [16]. When the brain receives a light stimulus it first interprets form as distinct from background. Figure-ground separation or pattern recognition is the first cognitive step in the process of perception. Color plays an important, but secondary role in recognition. Color responses are more tied to human emotions than to his intellect. Just this property makes the colors very powerful source of influence of human perception. The presence of one or more colors in different proportions conveys different messages, which can increase or suppress the perception of the observed objects.

A. Color

The nature of color is in the focus of research by different science disciplines – Physics studies the power essence of the color, Physiology is interested in the process of human eyes perception of specific wavelengths and theirs transformation to color, Psychology examines the problems of colors' perception and theirs influence on the mentality, Mathematics suggests methods for color measurement. The enormous growth of the number of digital images and videos in different application areas explains the extensive interest in developing computer science methods in this area.

Different models for presenting the color have been created from Antiquity. A detailed survey of color models was made by the team of Urs Baumann [17]. Different models serve various domains – from Physics and Colorimetry; through Painting, Architecture, and Design; to Digital coding for printers, monitors and TV. The history and practice show that a perfect color model cannot be created: one is suitable to supply compact coding and transmitting of the color characteristics, another is easy perceived from humans, etc.

From human point of view, it is most easy to define the color as composition of three components – hue, saturation and lightness. Hue means the name of the color – red, orange, etc. Black, grays and white are called achromatic. Saturation measures the hue intensity or brilliance of a sample, its dullness or vividness. Lightness refers to relative light and dark in a sample [16]. Such point of view to the color facilitates the structuring of color harmonies and contrasts are evinced in art images.

B. Harmonies and Contrasts

The contrasts are experienced when we establish differences between two observed effects. When these differences reach maximal values we talk about diametrical contrast. Our senses perceive only on the base of comparison. For instance one segment is short when lays near long segment and vice versa. In similar way color effect becomes strong or weak thorough contrasts.

The color combinations called "harmonious" in common speech usually are composed of closely similar hues, or else of different colors in the same shades. They are combination of colors that meet without sharp contrast. As a rule, the assertion of harmony or discord simply refers to an agreeable-disagreeable or attractive-unattractive scale.

Many people are observed and examined the influence of the color each other. Aristotle in his "De meteorologica" posed questions about different looking of violet near to white wool and black wool [18]. His questions were systematically examined and explained later by Michel Eugène Chevreul.

In 1772 – the same year that Johann Heinrich Lambert constructed his color pyramid and demonstrated for the first time that the complete fullness of colors can only be reproduced within a three dimensional system [19], another color circle was published in Vienna by Ignaz Schiffermüller. He was one of the first, who arranged the complementary colors opposite one another: blue opposite orange; yellow opposite violet; red opposite green [18].

Leonardo da Vinci (1452-1519) had probably been the first to notice that when observed adjacently, colors will influence each other. Goethe, however, was the first who specifically draw attention to these associated contrasts.

Michel Eugène Chevreul (1786-1889) had continued resolving the questions for contrast with establishing a law of "Simultaneous Contrast" [18]. When colors interact, they are capable of changing in appearance, depending on particular relationships with adjacent or surrounding colors. Simultaneous contrast is strongly tied to the phenomenon of afterimage, also known as "Successive contrast", when the eye spontaneously generates the complementary color even when the hue is absent. The explanation of successive contrast is given in opponent color vision theory, which acquired its integral view in the works of Ewald Hering in 1872 [18]. Successive and simultaneous contrast suggest that the human eye is satisfied, or in equilibrium, only when the complemental relation is established.

The great contribution in revealing effects of color interactions has Josef Albers (1888-1976). His book "The Interaction of Color" [20] has proven key to understanding color relationships and human perception. Albers stated that one color could have many "readings", dependent both on lighting and the context in which the color is placed. He felt that the comprehension of color relationships and interactions was the key to gaining an eye for color. According to Albers, we rarely see a color that is not affected by other colors. Even when a color is placed against a pure neutral of black, white, or gray, the color is influenced by that neutral ground. Colors interact and are modified in appearance by other colors in accordance with three guiding rules: *Light/dark value contrast*, *Complementary reaction*, and *Subtraction*.

Johannes Itten (1888-1967) continued theories of Albers. He was one of the first to define and identify strategies for successful color combinations [21]. Through his research he devised seven methodologies for coordinating colors utilizing the hue's contrasting properties. These contrasts add other variations with respect to the intensity of the respective hues; i.e., contrasts may be obtained due to light, moderate, or dark value. He defined the following types of contrasts: *Contrast of hue*, *Light-dark contrast*, *Cold-warm contrast*, *Complementary contrast*, *Simultaneous contrast*, *Contrast of saturation*, and *Contrast of extension (proportion).*

C. Artists' color wheel

Usually, in accordance of Johannes Itten proposition, the color wheel, which represents relations between hues, is divided in twelve sections. Centers of three equidistance sections correspond to primary colors. Between them secondary colors are posed, which from one side are middle points of two primary colors, and from other side are complementary to the third color. The quantization is expanded with the intermediate colors, which lays at midpoint to adjacent primary and secondary hues.

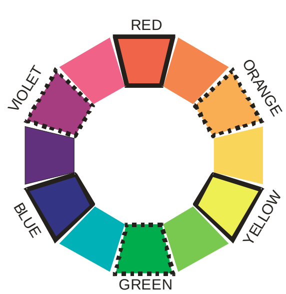


Figure 1. Standard artists' color wheel

In Figure 1 the position of the hues in standard artists' color wheel is shown. This order and correlations between hues is described in RYB (Red-Yellow-Blue) color model, used by the artists. Let us mention that this arranging of hues differs from many of contemporary color models – RGB (Red-Green-Blue), CMY (Cyan-Magenta-Yellow), HSL (Hue-Saturation-Luminance), HSV (Hue-Saturation-Value), based on the defining of colors as primary or secondary in accordance with trichromatic theory [22].

IV. Classification of Harmonies and Contrasts

We present one classification of different types of harmonies and contrasts, from the point of view of the three main characteristics of the color – hue, saturation and lightness.

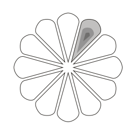
A. Harmonies/contrasts from point of view of hue

There can be examined two different types of harmonies/contrast: ones that take into consideration only disposition of hues each other and others that account exact hue values and their influence on the human perceiving.

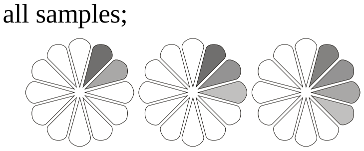
1) Hue harmonies/contrasts based on the disposition of hues

The figures below shows only relatively disposition of the colors, not the absolute meaning of the color. Some of these combinations are discussed in [16] and [23].

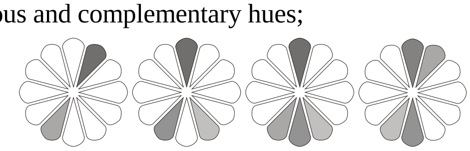
a) Monotone compositions: These compositions use one hue, and image is built on the base of varying of lightness of color. These images are used to suggest some kind of emotion since every hue bears specific psychological intensity;



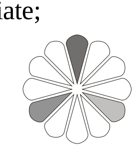
b) Analogous hues: Analogous hues can be defined as groups of colors that are adjacent on the color wheel; contain two, but never three primaries and have the same hue dominant in all samples;



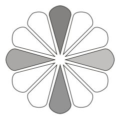
c) Complementary contrasts: Complementary colors are hues that are opposite one another on the color wheel. When more than two colors take part in the composition the harmonic disposition suggests combination between analogous and complementary hues;



d) Triads: Three colors that are equidistance on the color wheel form triad. This means that all colors are primary or secondary, or intermediate;



e) Tetrads: The tetrad includes four colors in equidistance on the color wheel. This contrast produces very complicated scheme and can lead to disharmony;



f) Achromatic compositions: As a special case, images composed by black, grays and white tones or contain colors with very small saturation.

2) Harmonies/contrasts based on the group of hues (Warm-cold contrast)

Warm and cold are two opposing qualities of hue. Warm colors are hues around red and orange; cold colors are these around blue. The terms warm and cold are helpful for describing families of colors. They can be defined as follows:

a) Warm: The image is warm when composition is built from family of warm colors;

b) Cold: By analogy – the image is cold when it is composed only (or predominantly) with cold colors;

c) Neutral: The composition contains colors mainly from neutral zones;

d) Warm-cold: The composition lays in this category when the percentage of cold family is in some proportion to the percentage of warm family;

e) Warm-neutral: In such compositions there is proportion between warm colors and neutral ones;

f) Cold-neutral: The image contains cold and neutral tones in some proportion.

Unlike of hue, which is circular and continuous, saturation and lightness are linear. That difference determines different definitions of harmonies for these characteristics.

B. Harmonies/contrasts from point of view of saturation

This harmony appears together with the hue ones. It is used to give different perception when the color is changed. As a whole we can define three big groups of harmonies and contrasts:

a) Dull: An image can be classified as dull when composition is constructed mainly from desaturated colors;

b) Clear: Clear images have been build mostly from clear (spectral and near to spectral, respectively only with varying in lightness) colors.

c) Different proportion of saturations: Usually in composition of clear colors in combination of dull ones. Depending on content of different saturation and of distance between predominate quantities harmonies can be defined such as *smooth*, *contrary*, etc.

C. Harmonies/contrasts from point of view of lightness

The whole effect of the lightness of the image as well as light-dark contrast is a very powerful tool in art mastering. Mainly, an artwork can not contain light-dark contrast – at that case the image has one integral vibration of the lightness. In other case sharp light-dark contrast is used to focus the attention in exact points of the image.

a) Dark: Dark compositions are built mainly from dark colors;

b) Light: Light images contain mostly colors near white;

c) Different proportion of lightness: Light colors combined with dark ones compose the image. Depending on content of different lightness and of distance between predominate quantities contrasts can be defined as*: smooth*, *contrary*, etc.

V. Experimental Software System Functionality

An experimental software system for automatic image descriptor annotation, which corresponds to defined harmonies and contrasts, was created in the frame of a virtual laboratory for semantic image retrieval APICAS.

We have used analyses of the images and artists' styles, made in [18][21][24][25][26] to tune up our algorithms and parameters.

For the purposes of the system we convert RGB-values of color of each pixel to values in non-uniformly quantized HSL-feature space – twelve hues plus one value for achromatic color, five levels of saturation and five levels of luminance are identified. The numbers of the layers are chosen on the base of Itten's color theory.

The system allows user definitions of the quantization of the space. Figure 2 shows the screen where the user can set up quantization for the purposes of further defining of color harmonies or contrasts. The screenshot is made when quantization of hue is in accordance with artists' color wheel. The displacement between correlation of hues in two color models – RYB and HSL is clearly seen. Current realization of defining hue dispositions is based on RYB color space.

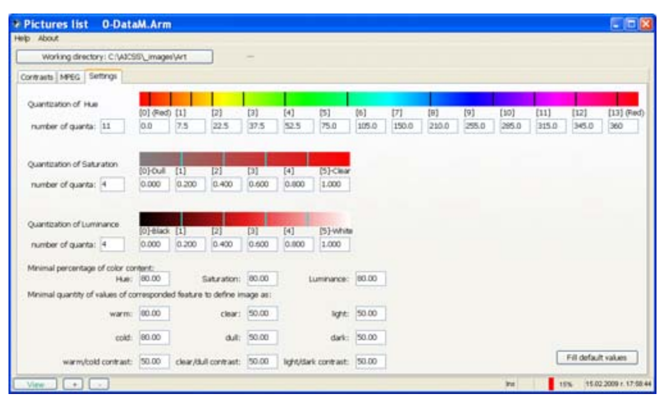


Figure 2. Screen for set up the quantization parameters and boundaries

The saturation and luminance are quantized in five levels. The boundaries can be set up by the user. By default, equal quantization is proposed.

In previous version [1] we have used exact function of defining the belonging of the color characteristic to quantizing segment. Now, quantization of colors is made using fuzzy calculating of belonging of color to corresponded index (Figure 3). If the position of examined value is in inner part of one defined segment (more than one half from the left bound and less than three half from the right bound) the characteristic is considered to belong to this segment. In other case (except the endmost parts for saturation and lightness), part of the characteristic is considered to belong to this segment and the rest part is considered to belong to the adjacent segment. For receiving that part a linear function, which reflects the decreasing of belonging of that characteristic to the segment, is used.

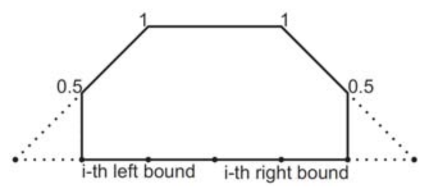


Figure 3. Fuzzy function for calculating quantization part of color characteristic

Taking into account our earlier examination of the distribution of color components in art paintings [27] we make normalization of the colors in respect of hue distribution (Figure 4). This normalization allows simplifying of comparing presence of color characteristic values in further stages.

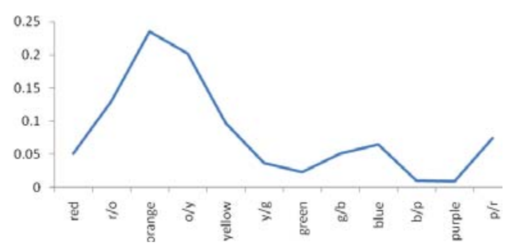


Figure 4. Average distribution of hue component in art paintings

As a result, every picture is represented with three dimensional array containing coefficients of participation of colors with correspondingly measured characteristics of the picture.

A={A(ih,is,il)|ih=-1,...,NH-1; is=0,...,NS-1; il=0,...,NL-1}

Here NH=12 and corresponds to the number of quantized colors in Ittens' circle. "-1" index percentage of achromatic tones; "0" to "NH-1" points percentage of colors, ordered as it is shown on Figure 1, starting from reds and ending to purples.

In our examination $NS=5$. Index "0" holds percentage of grays and almost achromatic tones, and "4" contains percentage of pure (in particular – spectral) tones.

For indexing of luminance we use $NL=5$ also. "0" holds percentage of very dark colors, and "4" contains percentage of very light colors.

On the base of this array for simplification of further calculation in some cases three arrays, containing percentage values of corresponding characteristics in the picture is calculated. These arrays are:

- H ($h_{-1}, h_0, \ldots, h_{NH-1}$) for hues;
- S ($s_0, \ldots, s_{NS-1}$) for saturation;
- L ($l_0, \ldots, l_{NL-1}$) for lightness.

A. Hue order vector

This vector contains number of dominant hues *nh*, and positions of dominant hues, ordered in decreasing percentage. *nh* can vary from zero for achromatic paintings, to maximal defined dominant colors. For the purposes of defining hue harmonies maximal dominant colors are restricted in this example to 5. When image is not achromatic the value of *nh* is defined as the number of ordered hues, which sum of the percentages exceed some (expert-defined) value *x*.

$(nh; p_1, p_2, \ldots, p_{nh}),$

$nh \in \{0, \ldots, 5\}$

$p_i \in \{-1, \ldots, NH-1\}$ and $h_{p_i} \geq h_{p_{i+1}}$, $i \in \{1, \ldots, nh-1\}$

$$nh: \begin{cases} nh = 1 \ \ if \ \ h_{p_1} \geq x \\ nh = n \ \ if \ \ \sum_{i=1}^{n-1} h_{p_i} < x \ \ and \ \ \sum_{i=1}^{n} h_{p_i} \geq x \end{cases}$$

B. Hue harmony/contrast, based on disposition

For defining hue harmonies/contrasts first we define:

$$opposite(p) = \begin{cases} p + NH \ div \ 2 \ \ if \ \ p \leq NH \ div \ 2 \\ p - NH \ div \ 2 \ \ if \ \ p \geq NH \ div \ 2 \end{cases}$$

$$l\_neighbour(p) = \begin{cases} NH - 1 \ if \ \ p = 0 \\ p - 1 \ if \ \ p \ \ in \{1, \ldots, NH-1\} \end{cases}$$

$$r\_neighbour(p) = \begin{cases} 0 \ if \ \ p = NH - 1 \\ p + 1 \ if \ \ p \ \ in \{0, \ldots, NH-2\} \end{cases}$$

$$l\_triad(p) = (NH + p - NH \ div \ 3) \mod NH$$

$$r\_triad(p) = (p + NH \ div \ 3) \mod NH$$

$$l\_tetrad(p) = (NH + p - NH \ div \ 4) \mod NH$$

$$r\_tetrad(p) = (p + NH \ div \ 4) \mod NH$$

The values of the hue harmony depend from the number of dominant hues *nh*:

- *nh*=0:

Achromatic: the composition is constructed by black, white and gray tones. This construction can be examined as special case of monochromatic harmony;

- *nh*=1:

Monochromatic: only one hue predominates in image;

- *nh*=2:

Analogous: when p_2=*l_neighbour*(p_1) or p_2=*r_neighbour*(p_1);

Complementary: when p_2=*opposite*(p_1);

Partial Triad: when p_2=*l_triad*(p_1) or p_2=*r_triad*(p_1);

- *nh*=3:

Analogous: if for one of dominant hues p_i ($i\in\{1,\ldots,nh\}$) is fulfilled that the other two colors are *l_neighbour*(p_i) and *r_neighbour*(p_i) respectively;

Split complementary: if for one of dominant hues p_i ($i\in\{1,\ldots,nh\}$) is fulfilled that the other two colors are *l_neighbour*(*opposite*(p_i)) and *r_neighbour*(*opposite*(p_i));

Triad: if for one of dominant hues p_i ($i\in\{1,\ldots,nh\}$) the other two colors are *l_triad*(p_i) and *r_triad*(p_i);

- *nh*=4:

Analogous: if for one of dominant hue p_i ($i\in\{1,\ldots,nh\}$) is fulfilled that one of the other three colors p_j ($j\in\{1,\ldots,nh\}$, $j\neq i$) p_j=*l_neighbour*(p_i) or p_j=*r_neighbour*(p_i) and other two colors are *l_neighbour*(p_j) and *r_neighbour*(p_j);

Double Complementary: if for one of dominant hue p_i ($i\in\{1,\ldots,nh\}$) is fulfilled that one of the other three colors p_j ($j\in\{1,\ldots,nh\}$, $j\neq i$) p_j=*opposite*(p_i) and other two colors are *l_neighbour*(p_i) and *l_neighbour*(p_j) or *r_neighbour*(p_i) and *r_neighbour*(p_j);

Split Complementary: if for one of dominant hue p_i ($i\in\{1,\ldots,nh\}$) is fulfilled that one of the other three colors p_j ($j\in\{1,\ldots,nh\}$, $j\neq i$) p_j=*opposite*(p_i) and other two colors are *l_neighbour*(p_j) and *r_neighbour*(p_j);

Tetrad: if for first hue p_1 the other hues are *l_tetrad*(p_1), *opposite*(p_1), *r_tetrad*(p_1) respectively;

- *nh*=5:

Multicolor: here can be searched the presence of defined combinations discarding one of the colors.

C. Cold/warm contrast

For defining cold/warm contrast the system compares percentage values of families of colors p_{warm}, p_{cold}, and $p_{achromatics}$. We have take into account the fact of changing the type of some color in dependency of its saturation and lightness [28]. Because of this we calculate the values of p_{warm}, p_{cold}, and $p_{achromatics}$ on the base of three-dimensional array A. The strongest contrasts points is the warmest "red-orange" (ih=1) and the coolest "blue-green" (ih=7). We use semi-linear function of including colors in warm, respectively cold family, whit following properties:

- all achromatic values (ih=-1) and very desaturated colors (is=0) are added to achromatic family;
- increasing the lightness in desaturated colors (is=1,2) leads to increasing of coldness. For instance dark desaturated colors is added in warm family from magenta to orange-yellow (ih in {11, 0, 1, 2, 3}), but from light ones only red and red-orange are added (ih in {0, 1}). Conversely, dark colors added to cool family are only these near blue-green (ih in {6, 7, 8}); increasing the light expands the range and in cool family from lightest yellow-green to lightest blue-magenta (ih in {5, 6, 7, 8, 9}) and half of neighbors are included (ih in {4, 10});
- colors with middle saturation (is=3) include stable families of warm colors (ih in {0, 1, 2, 3}) and cold colors (ih in {6, 7, 8});
- for saturated colors (is=4) increasing the lightness cause expanding of both families of warm and cold colors. For instance for dark saturated colors in warm family belongs from magenta to orange-yellow (ih in {11, 0, 1, 2, 3}), while in light spectrum half of their neighbors also are included (ih in {10, 4}).

The image is defined as *warm*, *cold*, or *neutral* if corresponding value is greater than some threshold. If none of these values exceeds given parameters, the image is *warm-cold*, *warm-neutral*, *cold-neutral* according to order of decreasing of corresponded values.

D. Saturation order vector

This vector contains number of dominant saturations *ns* ($ns\in\{1,\ldots, NS\}$), and positions of dominant saturations, ordered in decreasing percentage. The value of *ns* is defined as the numbers of ordered saturations, which sum of the percentages, exceed some value *y*.

(ns; $p_1, p_2, \ldots, p_{ns}$),

$ns\in\{1, \ldots, NS\}$

$p_i \in\{0, \ldots, NS\text{-}1\}$ *and* $s_{p_i} \geq s_{p_{i+1}}$, $i\in\{1, \ldots, ns\text{-}2\}$

$$ns:\begin{cases} ns=1 \;\; if \;\; s_{p_1} \geq y \\ ns=n \;\; if \;\; \sum_{i=1}^{n-1} s_{p_i} < y \;\; and \;\; \sum_{i=1}^{n} s_{p_i} \geq y \end{cases}$$

E. Saturation combinations

If *ns*=1 the picture is defined as *monointense*. If *ns*>1 some combinations of presence of dominant saturations can be outlined. For instance, if p_0 and p_{NS-1} are dominant saturations, the image can be defined as *contrary*; if saturations are adjoining – the feature is *smooth*, etc.

F. Clear/dull contrast

Depending of the global lightness of the image the saturation distribution of the image is possessed in another attribute, which can receive values as *soft* or *sharp* for light images, *ground* or *spectral* for images with medium lightness and *dull* or *clear* for dark images.

G. Lightness order vector

This vector (nl; p_1, p_2, …, p_{nl}) is defined in the same way as the saturation order vector. It contains number of dominant lighting values nl ($nl \in \{1, \ldots, NL\}$), and their positions, ordered in decreasing percentage.

H. Lightness combinations

These values are defined in the equal manner as saturation ones – the same function are used; only corresponding parameters are changed.

I. Light/dark contrasts

The attribute, which receives values for light-dark contrast depends of user defined threshold of darkness and lightness. The images, which hold l_0 more than given dark threshold, are identified as *very dark*. *Dark* images are these for which l_0+l_1 exceed this threshold. Similarly, the images with l_4 receive value *very light* and these for which l_3+l_4 exceed the threshold are *light*. Depending of distribution of lightness, images can be categorized as *dark-light*, *light-dark*, *middle*, etc.

VI. Experimental Software System Realization

The proposed tools for automatic annotation of the images with harmonies' and contrasts' descriptors are realized as part of a virtual laboratory for image retrieval "Art Painting Image Color Aesthetic and Semantic" (APICAS).

A. Data entry

The system operates with images in JPEG-format. Images, stored in one directory, form a collection.

The user can choose the specific collection by changing the working directory. The system automatically scans the collection and extracts features. The user can refine setting of some parameters or boundaries (see Figure 2), which provoke recalculating of the corresponded descriptors.

The files, used in these collections, contain in their names the information about the artist and the name of the stored painting. The system extracts the names of the picture and the artist and, using a small thesaurus with information about the artists (dates of birth and death; countries; movement; periods), connects these metadata, extracted by the context, to information for the pictures. This way for automatic metadata extraction is applied in order to ensure easy way for making the experiments and analyzing the results.

B. Access

The extracted descriptors (from the content and from the context) can be observed in a grid. The user can sort it by any selected feature. Pointing on the exact image, the user can see all extracted metadata, connected to this image – an example is given on Figure 5.

Figure 5. Results of calculating of types of harmonies/contrasts for the picture "Annunciation" by Botticelli

The user can set different conditions on the extracted descriptors and receive the images that satisfy these conditions. The results can be obtained in two forms:

- in thumbnail form, where the images can be seen. An example of such result is shown on Figure 6;
- in a file, where selected images can be additionally batched using other features, selected by user.

The system allows searching within a collection of images, which has specific combination of the colors, defined by some harmony or contrast.

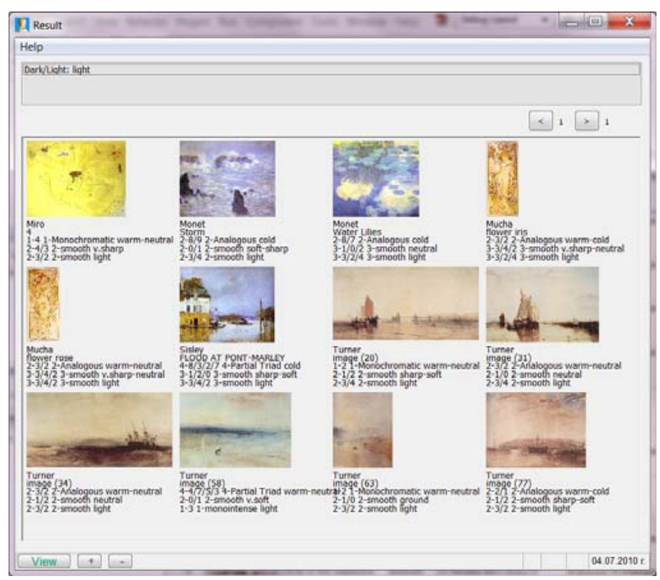


Figure 6. Result of retrieval from the image base with parameter: "Dark/light contrast = Light"

Another part of the system allows creating a datasets, containing extracted attributes or selected part of them labeled with chosen profile such as artist name, movement, scene-type. These datasets can be used for further analysis by data mining tools for searching typical combinations of characteristics, which form profiles of artists or movements, or reveal visual specifics, connected to the presented thematic in the images.

VII. Experiment Results

For our experiments we have used a dataset that includes 600 paintings of 18 artists from different movements of West-European fine arts and one group, which represent Orthodox Iconographic Style from Eastern Medieval Culture (Table 1). The paintings were chosen by an art expert reviewer. He has included in the collection the most valuable paintings for every movement. The pictures were obtained from different web-museums sources using ArtCyclopedia as a gate to the museum-quality fine art on the Internet [29].

TABLE I. List of the artists, which paintings were used in experiments, clustered by movements

Movement	Artist
Icons (60)	Icons (60)
Renaissance (90)	Botticelli (30); Michelangelo (30); Raphael (30)
Baroque (90)	Caravaggio (30); Rembrandt (30); Rubens (30)
Romanticism (90)	Friedrich (30); Goya (30); Turner (30)
Impressionism (90)	Monet (30); Pissarro (30); Sisley (30)
Cubism (90)	Braque (30); Gris (30); Leger (30)
Modern Art (90)	Klimt (30); Miro (30); Mucha (30)

A. *Distribution of some harmonies/contrasts in art paintings*

Here some examples of distribution of defined features by movements or artists styles are presented.

In these experiments we have used HSL-artist color model with fuzzy calculating of belonging of color to corresponded index.

Figure 7 shows the distribution of images from different movements, based on cold/warm contrast. The high predominance of warm paintings in ICON style can be explained with the orthodox tradition for using gold paints as well as red color, which is main symbol of sacrificing and martyrdom. The big presence of dark warm colors is specific for the Baroque. Presenting the nature in paintings is typical for the Romanticism, which leads to forcing the presence of cold (green and blue) tones. This tendency increases in the Impressionism. Intensive study of nature led the Impressionists to an entirely new color rendition. Study of sunlight, which alters the local tones of natural objects, and study of light in the atmospheric world of landscape, provided the Impressionist painters with new essential patterns [21].

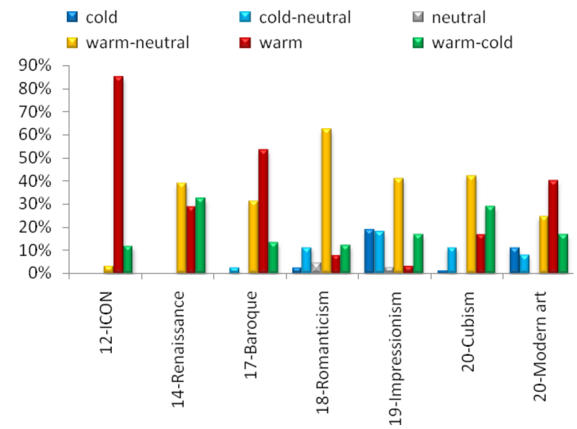


Figure 7. Distribution of paintings, grouped by movements, based on cold/warm contrast

Figure 8 shows the distribution of lightness in paintings from different movements. The big presence of dark colors and dark-light contrast is typical for Baroque. This is connected with using the techniques of oil-paints, which gives very deep dark effects in the paintings from one side and with typical using of light-dark contrast in this movement. This fact is connected not only with searching of maximal expression with applying this tool in the paintings, but also with the practice of this epoch to paint in the candle lights in studios [18].

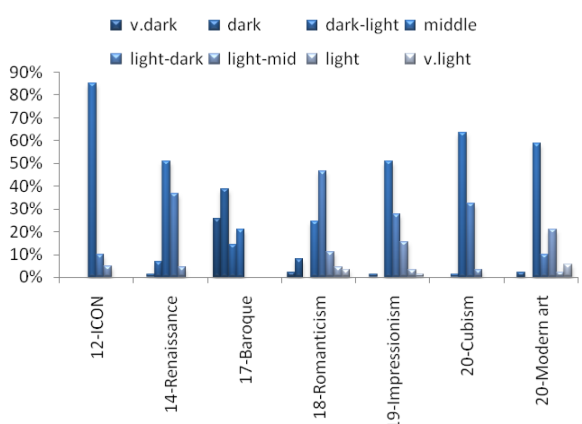


Figure 8. Lightness distribution of paintings, grouped by movements

Figure 9 shows the distribution of images in different movements, based on the first dominant hue. As we have observed in our previous work [27] the colors around orange are frequently dominant colors in the paintings in classic art. More modern movements tend to use different colors as dominant.

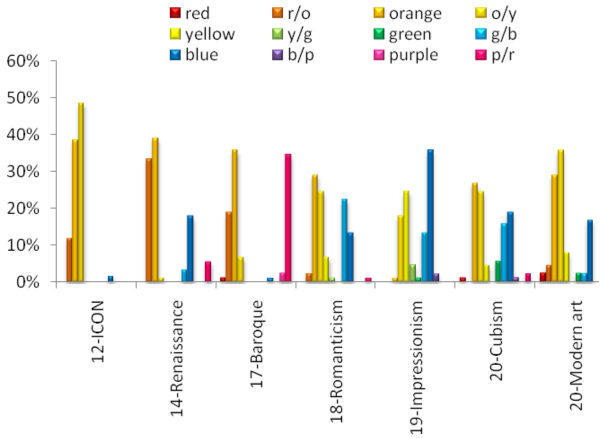


Figure 9. Distribution of paintings, grouped by movements, based on first dominant hue

Figure 10 shows the distribution of hue contrasts in the paintings, clustered by authors.

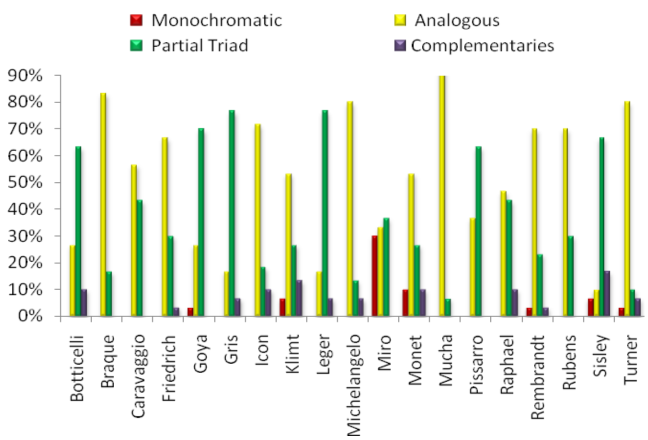


Figure 10. Percentage of different hue contrasts in the paintings of examined movements

As we can see partial triads are used in a lot of cases of natural paintings, for instance Pissarro and Sisley. The triads exist in paintings with scene presentation from authors, which techniques are based mainly on hue contrasts, such as Botticelli and Goya. Monochromaticity and analogous harmonies are presented in artworks of painters, where other key expressions are used, for instance light-dark contrast in Baroque artists, gradient expressions in Braque style, Miro's abstract paintings, etc. [26].

B. Analysis of combination of defined features

The collective of Institute of Mathematics and Informatics in Bulgarian Academy of Sciences has created data mining environment system PaGaNe [30]. Using the associative rule miner, realized in PaGaNe we have made more complicated analysis for extracting combinations of extracted features typical for examined artists. For instance, for more than one third of paintings, combinations of four attributes are presented in Table II.

TABLE II. COMBINATIONS OF FOUR ATTRIBUTES, WITH MORE THAN 33.33% SUPPORT FOR EXAMINED ARTISTS

Artist	4-items combinations	support
CARAVAGGIO	Sat. Harmony =3-SMOOTH Lum. Harmony =2-SMOOTH Warm-cold contrast =WARM-NEUTRAL Clear-dull contrast =CLEAR-DULL	33.33
GRIS	Hue Harmony =PARTIAL TRIAD Sat. Harmony =4-VARIETY Lum. Harmony =3-SMOOTH Dark-light contrast =MIDDLE	36.67
GRIS	Hue Harmony =PARTIAL TRIAD Lum. Harmony =3-SMOOTH Clear-dull contrast =SPECTRAL-GROUND Dark-light contrast =MIDDLE	33.33
ICON	Hue Harmony =ANALOGOUS Lum. Harmony =3-SMOOTH Warm-cold contrast =WARM Dark-light contrast =MIDDLE	35.00
ICON	Hue Harmony =ANALOGOUS Sat. Harmony =3-SMOOTH Warm-cold contrast =WARM Dark-light contrast =MIDDLE	31.67
MUCHA	Hue Harmony =ANALOGOUS Sat. Harmony =3-SMOOTH Lum. Harmony =3-SMOOTH Warm-cold contrast =WARM	36.67
MUCHA	Hue Harmony =ANALOGOUS Sat. Harmony =3-SMOOTH Lum. Harmony =3-SMOOTH Clear-dull contrast =SPECTRAL-GROUND	33.33
MUCHA	Hue Harmony =ANALOGOUS Lum. Harmony =3-SMOOTH Warm-cold contrast =WARM Clear-dull contrast =SPECTRAL-GROUND	33.33
RUBENS	Hue Harmony =ANALOGOUS Sat. Harmony =3-SMOOTH Lum.Harmony =2-SMOOTH Warm-cold contrast =WARM	33.33
REMBRANDT	Hue Harmony =ANALOGOUS Warm-cold contrast =WARM Clear-dull =CLEAR-DULL Dark-light =DARK	40.00
REMBRANDT	Warm-cold contrast =WARM Hue harmony =ANALOGOUS Clear-dull contrast =CLEAR-DULL Sat. Harmony =1-MONOINTENSE	36.67
REMBRANDT	Warm-cold contrast =WARM Clear-dull contrast =CLEAR-DULL Lum. harmony =1-MONOINTENSE Dark-light =DARK	33.33

Such approach of extracting rules from frequent datasets as well as their extension in the direction of class association algorithms can be used for defining semantic profiles of observed phenomena – movement, artists style or thematic, connected with abstract space of the taxonomy of the art image content, discussed by T. Hurtut [5].

VIII. Conclusion and Future Work

In this article we presented a novel and more complete classification of color harmonies by three main characteristics of the color, which is most close to the human perception. We used this classification in a designated software tool, which extracts the defined features from an image.

The next step will be to extend these concepts, adding texture features, which will allow us to address additional definitions of contrasts, presented in Ittens' theory.

One of the directions for future work will be to conduct experiments for the educational use of the resource and build a service, which could be included in a virtual learning environment and will allow student to search for similar images.

Another future application of the method and tool presented in the article is to integrate it in image databases as a service for generation of tags for use within Web 2.0 services. The huge amount of digital objects and the metadata bottleneck are well known; such a system will not produce the human social tagging but could generate image-characteristics tags like ‘greenish’, ‘scarlet’, ‘pale’, ‘dark’, which will be useful in image searches.

This makes the presented tool a natural component within the virtual laboratory for semantic image retrieval. The work presented here provides a good basis for these subsequent developments.

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