Chapter 4:

APICAS – Content-Based Image Retrieval in Art Image Collections Utilizing Colour Semantics

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1 Colour – Physiology and Psychology

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 [Holtschue, 2006]. When the brain receives light stimulus, it first recognizes shapes and objects and separates the objects from their surrounding environment. Figure-ground separation or pattern recognition is the first cognitive step in the process of perception. In this process, colour plays an important but secondary role. Colour responses are tied stronger to human emotions than to intellectual judgement. Even this property on its own illustrates why colours have such a powerful influence on human perception. The presence of one or more colours in different proportions conveys different messages, which can increase or suppress the perception of the observed objects.

Jointly with shape, colour is one of the fundamental building blocks of visual symbols. It is also closely associated with mental and emotional states, and can affect them profoundly [O'Connel et al, 2009].

Colours play a major role in the field of image retrieval. Within this context it is not the colour itself but the perception of colours and colour combinations as similar or dissimilar what is crucial when one has to extract images by some criterion related to the level of emotional perception, or to search for the specifics of expressiveness of the artist. All these tasks fall in already discussed abstraction aspects of image content. For instance, different painting techniques reflect technical abstractions, as well as the use of colour combinations as particular expressive means grounded on emotional abstractions.

Here we make an overview of the existing qualitative descriptions of the phenomena, which we will use later to propose an appropriate transition to quantitative formal description of successful colour combinations already defined by artists and art researchers.

The nature of colour is a subject of study in various sciences. Physics studied electromagnetic structure of light waves, physiology is interested in the perception of light waves as colours, psychology explores the problems of colour perception and its impact on intelligence, mathematics constructs techniques for structuring colour spaces and their measurement.

It appears that the basic laws for the establishment of harmony, colour, different ways to use contrast, the ratio of colour components with other forms of art such as line, plastic, lights, etc., which in theory and practice of painting are born intuitively, have scientific explanations in different disciplines (which does not mean of course that creating of the masterpiece is a simple process of following any schemes blindly).

The problems of colour can be examined from several aspects. The physicist studies the nature of the electromagnetic energy vibrations and particles involved in the phenomenon of light, the several origins of colour phenomena such as prismatic dispersion of white light, and the problems of pigmentation. He investigates mixtures of chromatic light, spectra of the elements, frequencies and wave lengths of coloured light rays. Measurement and classification of colours are also a topic in physical research. The chemist studies the molecular structure of dyes and pigments, problems of colour fastness, vehicles, as well as preparation of synthetic dyes. Colour chemistry today embraces an extraordinarily wide field of industrial research and production. The physiologist investigates the various effects of light and colours on our visual apparatus – eye and brain – and their anatomical relationships and functions. Research on light and dark adaptation and on chromatic colour vision occupies an important place. The phenomenon of afterimages is another physiological topic. The psychologist is interested in the influence of colour radiation on human mind and spirit. Colour symbolism, and the subjective perception and discrimination of colours, are important psychological problems. Expressive colour effects – what Goethe called ethico-aesthetic values of colours – likewise fall within the psychologist's research [Itten, 1961]. Cultural studies and semiology are both concerned with the meaning and interpretation of colours in different cultures. Engineering is investigating what are the best ways of generating high quality colours in different devices – starting from television and ending with small portable devices. The artist, finally, is interested in colour effects from their aesthetic aspect, and needs both physiological and psychological information.

Discovery of relationships, mediated by the eye and brain, between colour agents and colour effects in man, is a major concern of the artist. Visual, mental and spiritual phenomena are multiply interrelated in the realm of colour and the colour art [Itten, 1961].

1.1 Physiological Ground of the Colour Perceiving

The colour of the physical point of view is part of the electromagnetic spectrum with a wavelength of 380 nm to 780 nm (usually rounded or between 400 nm and 700 nm). The colour of an object depends on both the physics of the object in its environment and the characteristics of the perceiving eye and brain. Two complementary theories of colour vision are the trichromatic theory and the opponent process theory.

- *Trichromatic Theory*

Great importance for the development of the colour theory is the Newton discovery in 1666 that white light is a mix of all colours of the spectrum. In 1801, Thomas Jung suggests the hypothesis that mixing only three primary colours can produce all colours. Later Hermann von Helmholtz elaborated on this theory with the assumption that in the retina of the human eye has receptors responding to the three primary colours and all colours are obtained by mixing these three colours with different intensities. The trichromatic theory has been confirmed experimentally in 1960, when three types of receptors were identified in the retina, preferentially sensitive to red, green and blue light waves.

- *Opponent Theory*

The idea of opponent theory emerged in the studies of Leonardo da Vinci about 1500. Similar views were expressed by Arthur Schopenhauer , but the first integral presentation of this theory had been proposed in the works of Ewald Hering in 1872 [Hering, 1964]. The theory suggests that there are three channels opposing each other: red against green, blue against yellow, and black against white (the latter channel is achromatic and carries information about variations of lightness). Responses to one colour of an opponent channel are antagonistic to those of the other colour. To put it in another way, there are certain pairs of colours one never sees together at the same place and at the same time. One does not see reddish greens or yellowish blues but does see yellowish greens, bluish reds, yellowish reds, etc. One practical example for this theory is the so-called after-image phenomenon: if one looks at a unique red patch for about a minute and then switches the gaze to a homogeneous white area he would see a greenish patch on the white area. In other words after-image will produce such colours that in combination with the first colour are neutral. The opponent theory was confirmed in the 1950s, when opposing colour signals were found in optical connections between the eye and brain. At that time a pair of visual scientists working at Eastman Kodak conceived a method for quantitatively measuring the opponent processes responses. Leo Hurvich and Dorothea Jameson invented the hue cancellation method to psychophysically evaluate the opponent processing nature of colour vision [Hurvich and Jameson, 1957].

Modern theories combine these two theories: the process starts by light entering the eye, which stimulates the trichromatics cones in the retina, and is further processed into three opponent signals on their way to the brain. More recent developments are in the Retinex theory, proposed by Edwin Land. Experiments show that people have a considerable amount of colour constancy (i.e. colours are perceived the same even under different illumination) [Gevers, 2001].

- *Colour Perception*

Colour perception is not an independent process and is influenced by conditions in which this act takes place. On the one hand a physical interference of waves leads to the perception of two colours as another one, which had been used by impressionists after the invention of new techniques of laying the paints. On the other hand, the perception of colour provokes mutual induction of the nerve processes; according to Pavlov, the law of mutual induction of nerve processes is one of the fundamental laws of the nerve physiology [Raychev, 2005]. Mutual induction in the perception of colour leads to a change in the perception of a given colour, depending on the stimuli in another part of the retina (simultaneous contrast) or stimuli applied earlier on the same spot of the retina (consecutive contrast).

Contrasting colour changes, resulting from the simultaneous operation of different colours, can be analysed through three main features characterizing the colour – hue, brightness and saturation. Exceptions are achromatic and monochromatic images that use only the contrast of brightness. The perception of colour depends largely on the background. Under its influence, colours are seen in other tints and shades.

The perception of achromatic colours, placed among chromatic ones, is also changing. Gray colour on a red background is perceived with a greenish hue, on a yellow background – with a bluish one, on a green – with a pinkish one, on a blue – with a yellowish, i.e. the colour hue of the object acquires the additional background colour.

The same principles are valid to consecutive contrast, but in this case cannot refer to the background and the object, but to preceding visual stimuli, which affect the next colour, laid in the same position of sight. This is a result of the colour eye fatigue. The result is a coherent image, which remains different depending on the length of preceding visual stimulus as well as on its colour composition.

1.2 Image Harmonies and Contrasts

The contrasts are experienced when we establish differences between two observed effects. When these differences reach maximum values we talk about diametrical contrast. Our senses perceive only through comparison. For instance an object is perceived as being short when it is near to a long object and vice versa. In a similar way colour effects become stronger or weaker thorough contrasts.

Multiple scholars observed and examined the influence of colours on each other. Aristotle in his "De meteorologica" formulated questions about the difference of violet near white or black wool [Gage, 1993].

In 1772 – the same year that Johann Heinrich Lambert constructed his colour pyramid and demonstrated for the first time that the completeness of colours can only be reproduced within a three dimensional system [Spillmann, 1992], another colour circle was published in Vienna by Ignaz Schiffermüller. He was one of the first who arranged the complementary colours opposite each other: blue opposite orange; yellow opposite violet; red opposite green [Gage, 1993].

Leonardo da Vinci noticed that when observed adjacent to each other, colours are influencing the perception. Goethe, however, was the first to specifically draw attention to these associated contrasts.

Johann von Wolfgang Goethe in his book Theory of Colours, published in 1810, studied the emotion and psychological influence of colours. His six-hue spectrum of colours remains the standard for artists even nowadays [Birren, 1981].

Michel Eugène Chevreul (1786-1889) had contributed to the study of contrast establishing the law of *simultaneous contrast* in 1839 [Gage, 1993]. When colours interact, they are capable of change in appearance, depending on particular relationships with adjacent or surrounding colours. Simultaneous contrast is strongly tied to the phenomenon of afterimage, also known as *successive contrast*, when the eye spontaneously generates the complementary colour even when the hue is absent. The explanation of successive contrast is given in opponent colour vision theory. Successive and simultaneous contrasts suggest that the human eye is satisfied, or in equilibrium, only when the complementary colour relation is established.

Research on the mutual influences of colours had strongly manifested in the studies of Georges Seurat who suggested the optical fusion theory, also called Pointillism or Illusionism. The theory behind this optical mixture was set out as early as in the 2nd century by Ptolemy who identified two ways of achieving optical fusion; one by distance where "the angle of vision formed by rays of light from the very small patches of colour was too small for them to be identified separately by the eye, hence many points of different colours seemed together to be the same colour" [Gage, 1993]. The other related to after images and moving objects. The use of this theory lays in the established new painting technique, firstly showed by Seurat in his painting "Sunday Afternoon on the Island of La Grande Jatte" in 1886. He called this phenomenon "Chromoluminarisme" or "Peinture Optique". The Pointillist technique consists of "placing a quantity of small dots of two colours very near each other, and allowing them to be blended by the eye at the proper distance" [Birren, 1981].

Adolf Hoelzel suggested seven contrast groups, based on his own understanding of the colour wheels. Every contrast marks some quality of colour perception. His contrasts are: (1) Contrast of the hue; (2) Light-Dark; (3) Cold-Warm; (4) Complementary; (5) Gloss-Mat; (6) Much-Little; (7) Colour-Achromatic [Gage, 1993].

The great contribution in revealing effects of colour interactions was made by Josef Albers (1888-1976). His book "The Interaction of Colour" [Albers, 1963] became quintessential in understanding colour relationships and human perception. Albers stated that one colour could have many "readings", dependent both on lighting and the context in which it is placed. He felt that the comprehension of colour relationships and interactions was the key to gaining an eye for colour. According to Albers, we rarely see a colour that is not affected by other colours. Even when a colour is placed against a pure neutral of black, white, or gray, it is influenced by that neutral ground. Colours interact and are modified in appearance by other colours in accordance with three guiding rules: *Light/dark value contrast*, *Complementary reaction*, and *Subtraction*.

Johannes Itten (1888-1967) expanded the theories of Hoelzel and Albers. He defined and identified strategies for successful colour combinations [Itten, 1961]. Through his research he devised seven methodologies for coordinating colours 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*: the contrast is formed by the juxtaposition of different hues. The greater the distance between hues on a colour wheel, the greater the contrast;
- *Light-dark contrast*: the contrast is formed by the juxtaposition of light and dark values. This could be a monochromatic composition;
- *Cold-warm contrast*: the contrast is formed by the juxtaposition of hues considered "warm" or "cold";
- *Complementary contrast*: the contrast is formed by the juxtaposition of colour wheel or perceptual opposites;
- *Simultaneous contrast*: the contrast is formed when the boundaries between colours perceptually vibrate. Some interesting illusions are accomplished with this contrast;
- *Contrast of saturation*: the contrast is formed by the juxtaposition of light and dark values and their relative saturation;
- *Contrast of extension* (also known as the *Contrast of proportion*): the contrast is formed by assigning proportional field sizes in relation to the visual weight of a colour.

1.3 Psychological Colour Aspects

The colour impact on people depends on many factors, where physical laws and physiology are only the beginning. Psychological perception plays an important role in this process which is influenced by the particular psychological state on the one hand, and by socio-cultural environment in which the character of a person is composed on the other hand. Perception of colour brings the whole emotional and mental identity of the observer, his/her intelligence, memory, ideology, ethics, aesthetic feelings and other sensations. These feelings as well as philosophical, religious and other aspects of the categories of colour perception are essential to its nature and create relative symbolic aspects of colour impression.

Using colour as a symbol dates back to antiquity. Simple natural feeling, caused by the colour, gradually had been canonized in a system of secular or religious symbols. Thus a deep stratification of religious, social, historical, moral, ethical, psychological, etc. symbolism occurs, which sometimes leads to impossibility to detect what is the primary affective value of a particular colour. Heraldry is a typical example of such formal system in which every colour and composition conditionally acquired some symbolic meaning [Raychev, 2005]. Such orderly system of colour symbols is built in within the liturgical system of the Catholic, Orthodox and Protestant churches in which each liturgical colour carries some message and importance and may be used only under certain circumstances. The white colour for example symbolizes innocence, purity and joy. The red colour symbolizes fire and blood, sacrifice and martyrdom. The green colour brings hope and life. The purple colour is associated with relaxation, contemplation and repentance. The pink colour marks moments of joy during periods of penance and fasting. The black colour is associated with sorrow and sadness. Gold is allowed during the holidays and is associated with praise and high mood [Goldhammer, 1981].

Such symbolic colour systems had been developed in almost all nations. For example, in China five colours: white, black, blue, yellow and red symbolize certain concepts and attributes of the objects of the world around us as the cardinal directions, seasons, weather events, taste, character features and others [Raychev, 2005].

There are general principles of psychological elements of colour perception regardless of the formation sources of conditional symbolic systems in different cultures. All phenomena in the field of psychological perception of colour, which cannot be explained as a direct result of the visual impression of colour, can find an explanation by way of association. Associations are built between factors which coexist constantly or frequently. For instance binding of green with the concept of hope is the result of constantly repeated relationship between green plants and hope for future good harvest. Associations can be strictly individual, for example the relationship between blue and the mother can arise only for a person whose mother is blue-eyed or wears blue most of the time, but by no means it can be a common association.

Adopted secular and religious symbolism of colour is reflected in art because of its social function. For example there is no reason to be surprised that in West European Renaissance works of art before Constable (1776-1837) missed green tones. The academic style of painting at that time has presented a green with brown tones with scarce presence of green. Red robes as a symbol of the martyrdom of Jesus seemed natural and in line with religious symbolism in the painting of El Greco "The disrobing of Christ (1583)".

2 Art Image Analyzing Systems

In the last 20 years, numerous research and development efforts addressed the image retrieval problem, adopting the similarity-based paradigm. The technical report made by Remco Veltkamp and Mirela Tanase in 2000 still remains a precise and comprehensive review of industrial systems developed since the beginning of the work on CBIR until the end of the previous century [Veltkamp and Tanase, 2000]. While earlier developments were focused on extracting visual signatures, the recent ones address mostly the efficient pre-processing of visual data as a means to improve the performance of neural networks and other learning algorithms when dealing with content-based classification tasks. Given the high dimensionality and redundancy of visual data, the primary goal of pre-processing is to transfer the original data to a low-dimensional representation that preserves the information relevant for the classification. The performance of the techniques is assessed on a difficult painting-classification task that requires painter-specific features to be retained in the low-dimensional representation.

Most existing specialized systems focus on artworks analysis techniques over digital imagery, e.g. virtual restoration of artworks (inpainting, fading colour enhancement, crack removal, etc.). Other issues addressed are aspects requiring specific technical expertise (authentication, cracks, and art forgeries).

However, our primary area of interest in this dissertation is the content based retrieval of artworks in databases, as well as specific artists' studies (colour palette statistics, creative processes, etc.) and art history investigation. The emotional and aesthetic charge is inextricably bound up with other components that create the whole presentation of the artwork. Hence, emotional based image retrieval has also its place in the review.

Although all CBIR systems have, generally speaking, a common task, they differ in their goals, depending on the specific needs for which they were created.

We examined following systems: *QBIC* [Flickner et al, 1995], *PICASSO system* [Del Bimbo and Pala, 1997], *Pictorial portrait database of miniatures of the Austrian National Library* [Sablatnig et al, 1998], *Painting classification system* [Keren, 2002], *Art historian system* [Icoglu et al, 2004], *Lightweight image retrieval system for paintings* [Lombardi et al, 2005], *Collage* [Ward et al, 2005], *Brushwork identification* [Marchenko et al, 2006], *M4ART* [Broek et al, 2006], *ACQUINE* [Datta et al, 2006], *MECOCO* [Berezhnoy et al, 2007], *MARVEL* [Natsev et al, 2007].

Some systems (such as QBIC, Collage, M4ART, etc.) are industrial systems which support the complete digital object lifecycle in the overall process of image retrieval. Such systems have to support a wide range of functions, starting from reaching the data from repository through feature extraction, creating and keeping metadata, building appropriate indexing techniques for easy access, providing a friendly user interface and accelerating relevance feedback, etc.

Others are experimental systems, aimed to study the ability of some features and/or algorithmic techniques to enhance image retrieval or to solve exact classification task. Such systems do not claim to be so comprehensive, but being at the frontier of the research they are more focused of studying particular concept or technique and in this way are of definite interest.

Returning to our goal – studying the ways for closing different kinds of gaps – on Figure 21 we show our vision of connection of some of reviewed systems with the taxonomy of art image content. Here we do not stop our attention of used features and algorithms within the process of analysis made by the systems. We are focused on resulting features or concepts, produced by the systems. For instance, all systems in the rectangle engage with the field of artistic practice studies and art history investigation, notwithstanding that all of them use different kinds of visual primitives.

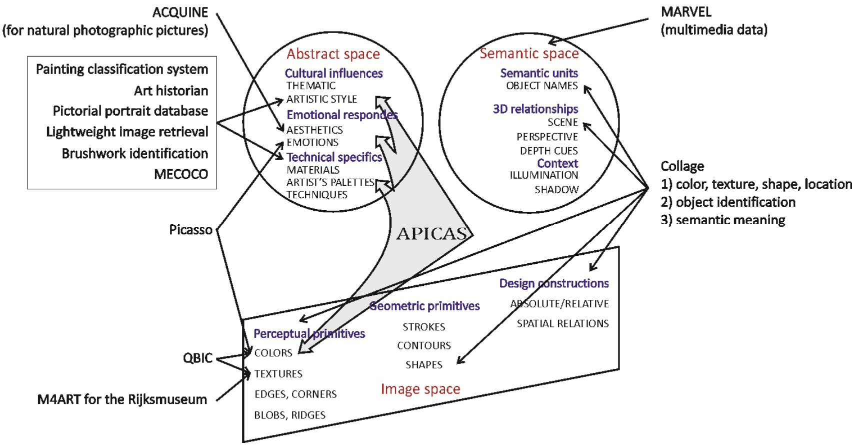


Figure 21. The systems and their connection with the taxonomy of art image content

In the figure we also incorporate our vision which shows which aspects will be addressed by our proposal, APICAS. APICAS is intended mostly to study the ability of colour analysis for covering mainly the abstraction gap. The analysis that we already made shows that colour plays a significant role in all three parts of abstraction space. The colour always brings some symbolism, generated by cultural environment. On the other side each artist builds his own colour vision, which expresses his/her emotional and aesthetic feelings. Technical aspects are also narrowed from current existence. For instance, the new painting direction in the landscapes of Impressionists for studying the air and sun influence arose after the industrial production of paints in tubes started; it allowed artists to work easily outside of their studios.

The scientific efforts are gradually progressing and step by step we can immerse into the processes of resolving the problems of classifying paintings of different styles or of different painters. New search paradigms such as mental image search with visual words enhance the user expression of visual target without a starting example. Alternatively, image fingerprinting, which deals with extracting unique image identifiers that are robust to image deformations (cropping, resizing, illumination changes, rotations etc.), might be used along with query-by-example techniques to partially deal with this task. This area is still in its infancy of research and development.

3 Proposed Features

We propose a set of visual features, with the aim to represent the human perception of colours. We try to formalize the qualitative achievements of Itten's theory of successful colour combinations. The Itten's investigation of the "subjective timbre" [Itten, 1961] shows that the existence of laws of combining the colours does not restrict the variety of used colour combinations by the artists. They are key to the identification of the individual's natural mode of thinking, being and doing.

We use three different categories of visual features, which represent the image (Figure 22).

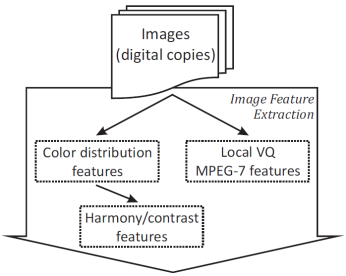


Figure 22. Proposed visual features

The first class of features is a group of several global colour low-level attributes, which represent colour distribution in the images. The analysis of the distribution of colour features in art images is made in order to be used in tuning up the similarity measure functions.

The second one is based on an attempt to formulate high-level features which represent colour harmonies and contrasts, based on the three main characteristics of the colour, which are closest to the human perception – hue, saturation and lightness. Functions for automatic features extraction from digital images based on the defined low-level global colour distribution features, are defined.

The third method for obtaining visual features consists of observing the tiles of the images from chosen learning set. MPEG-7 descriptors for these tiles are extracted. For each descriptor after clustering a set of centroids is defined. The new images are putted under similar splitting and the calculation of MPEG-7 descriptors is attached to the closest centroid from the corresponding cluster set. In this way we overcome the complexity of MPEG-7 descriptors, which made good presentation of different types of visual features but need specific processing and cannot be putted directly into generic classification algorithms.

3.1 Colour Distribution Features

These features represent colour distribution in the images. One popular way is to use colour histograms, which are a statistic that can be viewed as an approximation of an underlying continuous distribution of colours' values.

We want to use these characteristics for two connected purposes:

- analyzing the colour distribution in art images;
- using these low-level features in the process of calculating higher-level colour harmonies and contrast features.

For representing colours we chose colour models that describe perceptual colour relationships and are computationally simple – such as HSV, HSL, HSL-artist colour models. HSV is used in MPEG-7 descriptors. HSL better reflects the intuitive notion of "saturation" and "lightness" as two independent parameters. HSL-artist colour model is a base for further development for defining colour harmonies and contrast characteristics. Later, except in the places, where is specially pointed, the term "lightness" is used as a collective concept for "Lightness" in HSL colour model, "Value" in HSV colour model or "Luma" in HSL-artist colour model depending on the colour model chosen.

Colour histograms represent the number of pixels that have colours in each of a fixed list of colour ranges that span the image's colour space, the set of all possible colours. The used colours in digital presentations of art paintings can receive almost all possible colour values; because of this we divide the dimensions of the colour model into appropriate numbers of ranges.

The pixels in the images are converted into one of the chosen colour model (preferably HSL-artist colour model). The quantization of Hue is made to 13-bins, $ih = -1,...,NH - 1$, $NH = 12$, where one value is used for achromatic colours ($ih = -1$) and twelve hues are used for fundamental colours ($ih = 0,...,NH - 1$). The quantization of Hue is linear equidistant when HSL colour model or HSV colour model is chosen. For HSL-artist colour model the quantization function is non-linear with respect to taking into account the misplacement of artists' colour wheel and Hue definition in HSL colour space. The quantization intervals are given in Figure 23.

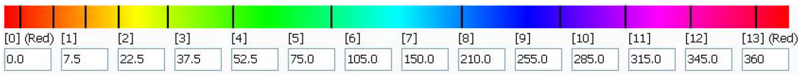


Figure 23. Quantization of Hue

The saturation and lightness in HSL colour model, respectively the saturation and values in HSV colour model, and saturation and luma in HSL-artist colour model are linearly quantized into NS-bins ($is = 0,...,NS - 1$), respectively NL-bins ($il = 0,...,NL - 1$).

The MPEG-7 Dominant Colour descriptor, which extracts a small number of representative colours and calculates the percentage of each quantized colour in the image, also can be used as a kind of colour distribution feature. In order to equalize further definitions we reconfigure extracted RGB-values of Dominant Colour descriptor into values in chosen quantized feature space and use the corresponded percentage of each quantized colour as a percentage in the defined three-dimensional array.

In [Ivanova and Stanchev, 2009] we have used exact function of defining the belonging of the colour characteristic to quantizing segment. Further in [Ivanova et al, 2010/IJAS] we add the possibility to make the quantization of colour characteristics using fuzzy calculating of belonging of colour to corresponded index (Figure 24). If the position of the examined value is in the 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 any 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 decrease of belonging of that characteristic to the segment, is used.

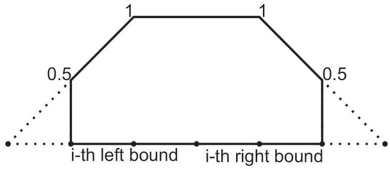


Figure 24. Fuzzy function for calculating quantization part of colour characteristic

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

$$A = \{A(ih, is, il) \mid ih = -1, \dots, NH - 1;\ is = 0, \dots, NS - 1;\ il = 0, \dots, NL - 1\}.$$

Analysis of colour distribution can be made by three directions together or only by two or one of them. On the base of three dimensional array A, using summarizing over the discarded dimension(s), we can receive corresponded projections:

- for examining two of the dimensions: $A_{HS} = \{A(ih, is, -)\}$, $A_{HL} = \{A(ih, -, il)\}$, $A_{LS} = \{A(-, is, il)\}$;
- for representing the distribution of one dimension: $A_H = \{A(ih, -, -)\}$, $A_S = \{A(-, is, -)\}$, $A_L = \{A(-, -, il)\}$

where $ih = -1, \dots, NH - 1;\ is = 0, \dots, NS - 1;\ il = 0, \dots, NL - 1$.

3.2 Harmonies/Contrasts Features

Usually, in accordance of Johannes Itten proposition, the colour wheel which represents relations between hues is divided into twelve sectors. The centres of three equidistance sections correspond to primary colours. Secondary colours are located between them, which from one side are middle points of two primary colours, and from other side are complementary to the third colour. The quantization is expanded with the intermediate colours, which lays at the midpoint to adjacent primary and secondary hues.

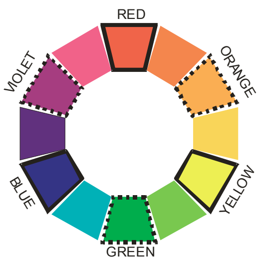


Figure 25. The Artists' Colour Wheel

In Figure 25 the position of the hues in standard artists' colour wheel is shown. This order and correlations between hues is described in RYB

(Red-Yellow-Blue) colour model, used by the artists. Let us mention that this arrangement of hues differs from many contemporary colour models – RGB (Red-Green-Blue), CMY (Cyan-Magenta-Yellow), HSL (Hue-Saturation-Luminance), HSV (Hue-Saturation-Value), being based on the definition of colours as primary or secondary in accordance with the trichromatic theory [Colman, 2006]. But all classic theories, connected with definition of contrast are based on the opposition of the colours as they appear in the artists' colour wheel.

We use HSL-artist colour model, which is based on the advantages of HSL and YCbCr colour models and render an account of disposition of hues in RYB colour model. We present one classification of different types of harmonies and contrasts, from the point of view of the three main characteristics of the colour – hue, saturation and lightness.

3.2.1 Harmonies/Contrasts from the Hue Point of View

- *Harmonies/Contrasts Based on the Hues Disposition*

The figures below shows only relatively disposition of the colours, not the absolute meaning of the colour. Some of these combinations are discussed in [Holtzschue, 2006] and [Eiseman, 2006].

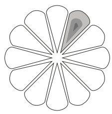


Figure 26. Monotone Composition

Monotone compositions: These compositions use one hue, and image is built on the base of varying of lightness of colour (Figure 26). These images are used to suggest some kind of emotion since every hue bears specific psychological intensity.

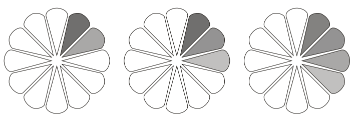


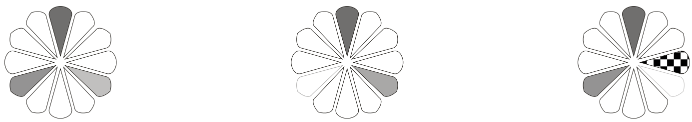
Figure 27. Different Variants of Analogous Composition

Analogous hues: Analogous hues can be defined as groups of colours that are adjacent on the colour wheel (Figure 27). They contain two, but never three primaries and have the same hue dominant in all samples.

a)Complementary; b)Double Complementary; c)Split Complementary; d)Complementary;

Figure 28. Variants of Complementary Contrast

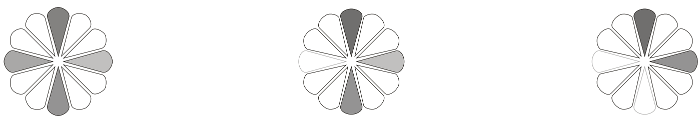
Complementary contrasts: Complementary colours are hues that are opposite one another on the colour wheel. When more than two colours take part in the composition the harmonic disposition suggests combination between analogous and complementary hues (Figure 28).



a)Triad; b)Partial Triad; c)Tweaked Triad;

Figure 29. Triads

Triads: Three colours that are equidistance on the colour wheel form triad. This means that all colours are primary or secondary, or intermediate. When we have analyzed art paintings also "partial" triads were observed in landscapes images, when two of colours, forming triad were founded as most significant for the image. In some cases a tweaked form of triads is observed also, when two of colours are in two of positions of triad, but the third one is a little skewed by the third position (Figure 29).



a)Tetrad; b)Partial Tertrad c)Partial Tetrad

Figure 30. Tetrads

Tetrads: The tetrad includes four colours in equidistance on the colour wheel. This contrast produces very complicated scheme and can lead to disharmony. Of course here also can be examined the presence of partial forms of the tetrads (Figure 30). Usually this scheme is used only with precisely coordinated saturation and lightness values in more schematic pictures, for instance in heraldic signs, flags, etc.

Achromatic compositions: As a special case, images composed by black, greys and white tones or contain colours with very small saturation.

➢ *Warm-Cold Contrast*

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

- *Warm:* The image is warm when the composition is built from family of warm colours;
- *Cold:* The image is cold when it is composed only (or predominantly) with cold colours;
- *Neutral:* The composition contains colours mainly from neutral zones;
- *Warm-cold:* The composition lays in this category when the percentage of cold family is in some proportion to the percentage of warm family;
- *Warm-neutral:* In such compositions there is proportion between warm colours and neutral ones;
- *Cold-neutral:* The image contains cold and neutral tones in some proportion.

3.2.2 Harmonies/Contrasts from the Saturation Point of View

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

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

- *Dull:* An image can be classified as dull when composition is constructed mainly from unsaturated colours;
- *Clear:* Clear images have been build mostly from clear colours (spectral and near to spectral, respectively only with varying in lightness);
- *Different proportion of saturations:* Usually in composition of clear colours 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.

3.2.3 Harmonies/Contrasts from the Lightness Point of View

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 the other case sharp light-dark contrast is used to focus the attention in exact points of the image.

– *Dark:* Dark compositions are built mainly from dark colours;
– *Light:* Light images contain mostly colours near white;
– *Different proportion of lightness:* Light colours 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.

3.3 Formal Description of Harmonies/Contrasts Features Using HSL-artist Colour Model

For defining colour harmonies/contrast features we use representation of the colour distribution as colour histograms, defined above:

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

Here $NH = 12$ and corresponds to the number of quantized colours in Ittens' circle. "-1" index percentage of achromatic tones; "0" to "$NH\text{-}1$" points percentage of colours, ordered as it is shown on Figure 25, starting from reds and ending to purples.

We use $NS = 5$ for defining harmonies' and contrasts' descriptors. Index "0" holds percentage of greys and almost achromatic tones, and "4" contains percentage of pure (in particular – spectral) tones.

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

To simplify further calculation up to three arrays, containing percentage values of corresponding characteristics in the picture is calculated on the basis of this array.

These arrays are (corresponded projections):

– $H(h_{-1}, h_0, ..., h_{NH\text{-}1})$ for hues ($A_H = \{A(ih, -, -)\}$, $ih = -1,...NH - 1$);
– $S(s_0, ..., s_{NS\text{-}1})$ for saturation ($A_S = \{A(-, is, -)\}$, $is = 0,...NS - 1$);
– $L(l_0, ..., l_{NL\text{-}1})$ for lightness ($A_L = \{A(-, -, il)\}$, $il = 0,...NL - 1$).

- *Hue Order Vector*

Hue Order 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 maximum values of defined dominant colours. For the purposes of defining hue harmonies maximum values of the dominant colours are restricted to 5. The value of nh is defined as the number of ordered hues, which sum of the percentages exceed some (expert-defined) value x when an image is not achromatic.

$(nh; p_1, p_2, ..., p_{nh})$, $p_i \in \{-1, ..., NH-1\}$: $h_{p_i} \geq h_{p_{i+1}}$, $h \in H$, $i \in \{1, ..., nh-1\}$

$nh \in \{0, ..., 5\}$:

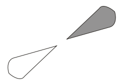
$$(nh = 0 \ \mathit{if} \text{ achromatic}); (nh = 1 \ \mathit{if} \ h_{p_1} \geq x); \left(nh = \min(n, 5) \ \mathit{if} \ \sum_{i=1}^{n-1} h_{p_i} < x \text{ and } \sum_{i=1}^{n} h_{p_i} \geq x \right)$$

- *Hue Harmony*

In order to define hue harmonies we first define functions which reflect the mutual disposition of two colours. Below we provide the mathematical formulation on the left side, and some graphical examples of defined disposition on the right. The dark leaf corresponds to the primary colour p, the light leaf shows relative disposition of the second colour, which is defined by corresponding function:

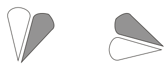
Colour, which lay opposite to the colour p:

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



Colour, which is left neighbour of the colour p:

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

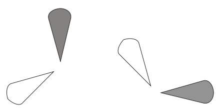


Colour, which is right neighbour of the colour p:

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

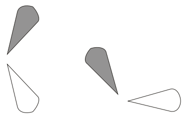
Colour, which can participate in triad with colour p, at its left side

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



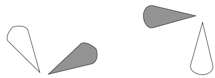
Colour, which can participate in triad with colour p, at its right side

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



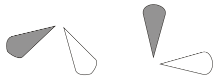
Colour, which can participate in tetrad with colour p, at its left side

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



Colour, which can participate in tetrad with colour p, at its right side

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



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

✓ $nh = 0$*:*

Achromatic: the composition is constructed by black, white and grey tones. This construction can be examined as a 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 $p_i,\ i \in \{1,...,nh\}$ is fulfilled that the other two colours are $l\_neighbour(p_i)$ and $r\_neighbour(p_i)$ respectively;

– *Split complementary:* if for one of dominant hues $p_i,\ i \in \{1,...,nh\}$ is fulfilled that the other two colours are $l\_neighbour(opposite(p_i))$ and $r\_neighbour(opposite(p_i))$;

– *Triad:* if for one of dominant hues $p_i,\ i \in \{1,...,nh\}$ the other two colours are $l\_triad(p_i)$ and $r\_triad(p_i)$;

✓ $nh = 4$:

– *Analogous:* if for one of dominant hue $p_i,\ i \in \{1,...,nh\}$ is fulfilled that one of the other three colours $p_j, j \in \{1,...,nh\}, j \neq i$: $p_j = l\_neighbour(p_i)$ or $p_j = r\_neighbour(p_i)$ and other two colours are $l\_neighbour(p_j)$ and $r\_neighbour(p_j)$;

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

✓ $nh = 5$:

– *Multicolour:* here the presence of defined combinations discarding the colour with smallest presence can be searched.

➢ *Cold/Warm Contrast*

For defining cold/warm contrast we use the proportion of the percentage values of families of colours p_{warm}, p_{cold}, and $p_{achromatic}$. We have taken into account the fact of changing the type of a colour depending on its saturation and lightness [Koenig, 2010]. Because of this we calculate these values using the 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 colours in warm, respectively cold family, with the following properties (Figure 31):

- All achromatic values ($ih \in \{-1\}$)are added to an achromatic family;
- All strongly unsaturated colours ($is \in \{0\}$) are added to an achromatic family;
- Increasing the lightness in unsaturated colours ($is \in \{1,2\}$) leads to increasing of coldness. For instance dark unsaturated colours are added in warm family from magenta to orange-yellow ($ih \in \{11,0,1,2,3\}$), but from light ones only red, red-orange, and orange are added ($ih \in \{0,1,2\}$). On the contrary, dark colours 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 halves of neighbours are included ($ih \in \{4,10\}$);
- Colours with middle saturation ($is \in \{3\}$) include stable families of warm colours ($ih \in \{0,1,2,3\}$) and cold colours ($ih \in \{6,7,8\}$);
- For saturated colours ($is \in \{4\}$) increasing the lightness cause expanding of both families of warm and cold colours. For instance for dark saturated colours in warm family belongs from magenta to orange-yellow ($ih \in \{11,0,1,2,3\}$), while in light spectrum half of their neighbours also are included ($ih \in \{4,10\}$). Cold colours also expands with half tones when the lightness increases.

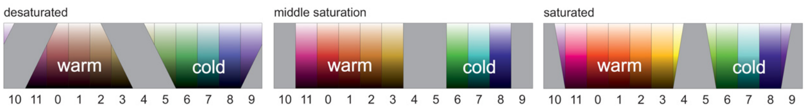


Figure 31. Cold/warm depending by saturation and lightness

An image is defined as *warm*, *cold*, or *neutral* if a 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.

➢ *Saturation Order Vector*

The Saturation Order 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 exceeds some value y.

$(ns; p_1, p_2, ..., p_{ns})$, $p_i \in \{0,...,NS-1\}$: $s_{p_i} \geq s_{p_{i+1}}$, $s \in S$, $i \in \{1,...,ns-1\}$

$$ns \in \{1,...,5\} : (ns = 1 \ \ if \ \ s_{p_1} \geq y) \ \text{or} \ \left(ns = n \ \ if \ \ \sum_{i=1}^{n-1} s_{p_i} < y \ \text{and} \ \sum_{i=1}^{n} s_{p_i} \geq y \right)$$

➢ *Saturation Combination*

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

➢ *Clear/Dull Contrast*

Depending of the global lightness of the image the saturation distribution of an 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.

➢ *Lightness Order Vector*

The Lightness Order 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, $nl \in \{1,...,NL\}$, and their positions, ordered in decreasing percentage. The value of nl is defined as the numbers of ordered values of lightness, which sum of the percentages exceeds some value z.

$(nl; p_1, p_2, ..., p_{nl})$, $p_i \in \{0,...,NL-1\}$: $l_{p_i} \geq l_{p_{i+1}}$, $l \in L$, $i \in \{1,...,nl-1\}$

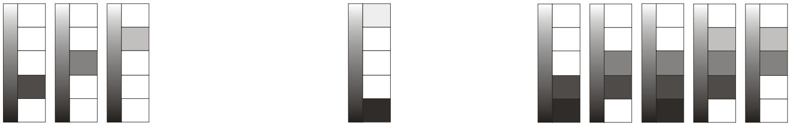
$$nl \in \{1,...,5\} : (nl = 1 \ \ if \ \ l_{p_1} \geq z) \ \text{or} \ \left(nl = n \ \ if \ \ \sum_{i=1}^{n-1} l_{p_i} < z \ \text{and} \ \sum_{i=1}^{n} l_{p_i} \geq z \right)$$

➢ *Lightness Combination*

The Lightness Combinations are defined in the equal manner as saturation ones where the same function are used and only corresponding parameters are changed.

When $nl = 1$ a picture is defined as *monointense* (Figure 32a). If $nl > 1$ some combinations of presence of dominant lightness can be outlined. If p_0 and p_{NL-1} are dominant lightnesses, the image is defined as *contrary*

(Figure 32b); if the lightnesses are adjoining – the feature is *smooth* (Figure 32c), etc.



a) monointense b) contrary c) smooth

Figure 32. Variants of lightness combinations

- *Light/Dark Contrast*

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_{NL-1} receive value *very light* and these for which $l_{NL-2} + l_{NL-1}$ exceed the threshold are *light*. Depending of distribution of lightness, images can be categorized as *dark-light*, *light-dark*, *middle*, etc.

3.4 Local Features, based on Vector Quantization of MPEG-7 Descriptors over Tiles

MPEG-7 descriptors are complex descriptors, which provide a good presentation of different types of visual features. The description of the structure of MPEG-7 descriptors and algorithms are given in [ISO/IEC 15938-3]. These complex structures need specific processing and cannot be put directly into generic classification algorithms. Here we give a brief explanation of each MPEG-7 descriptor examined in our work and which values we use in the further processing:

- *Scalable Colour (SC)* represents the colour histogram in the HSV colour space, encoded by a Haar transformation. For presenting the image or a selected part, *Scalable Colour* needs a vector with 64 attributes;
- *Colour Layout (CL)* specifies the spatial distribution of colours using *YCbCr* colour space. We use the first quantized *DCT* coefficient of the *Y*, *Cb* and *Cr* components, the next five successive quantized *DCT* coefficients of the *Y* component and the next two coefficients of the *Cb* and *Cr* component. These coefficients are used to form three vectors, which contain all extracted values of the *Y*, *Cb* and *Cr* components:

$$DY = \{DY_y; y = 1..6\} \;\; DY_y = \begin{cases} YDCCoeff & y = 1 \\ YACCoeff_{y-1} & y \neq 1 \end{cases}$$

$$DCb = \{DCb_y; y = 1..3\} \;\; DCb_y = \begin{cases} YDCbCoeff & y = 1 \\ YACbCoeff_{y-1} & y \neq 1 \end{cases}$$

$$DCr = \{DCr_y; y = 1..3\} \;\; DCr_y = \begin{cases} YDCrCoeff & y = 1 \\ YACrCoeff_{y-1} & y \neq 1 \end{cases}$$

Thus, the *Colour Layout* vector has 12 attributes;

– *Colour Structure (CS)*, which specifies both colour content and the structure of the content. The descriptor expresses local colour structure in an image by means of a structuring element that is composed of several image samples. We use a vector with 64 attributes for representing the *Colour Structure*;
– *Dominant Colour (DC)*. We reconfigured the presentation of this descriptor as three vectors, representing distribution of quantized hue, saturation and luminance. Such method is already precisely described and used by us in [Ivanova and Stanchev, 2009]. After this quantization we receive a vector with 23 attributes (13 for hue + 5 for saturation + 5 for luminance);
– *Edge Histogram (EH)* specifies the spatial distribution of five types of edges in local image regions (four directional edges – vertical, horizontal, 45 degree, 135 degree and one non-directional). *Edge Histogram* descriptor produces a vector with 80 attributes;
– *Homogeneous Texture (HT)* characterizes the region texture using the energy and energy deviation in a set of frequency channels. A vector with 60 attributes is used, presenting *Energy* and *Energy Deviation*.

As a result using these descriptors, we obtain a vector, which contains altogether more than 300 attributes. From other side each descriptor needs specific similarity measure. Some of the MPEG-7 descriptors are alternative. Scalable Colour, Colour Layout, Colour Structure and Dominant Colour concern different aspects of the same phenomenon, i.e. distribution of the colour within the image or region. It means that not all descriptors have to be used in the classification process. One of our tasks is to examine which are most for extracting simple visual features for the purposes of class recognition.

Visual attributes can represent global characteristics concerning whole images, or they can be extracted over the part of the images (specific region or tile of the image). Both approaches have their strengths: global attributes deliver integral temper of the image. Local attributes can capture more detailed information, which characterize the artists' styles or movements' specifics but introduce redundancy for the classifier. For reducing the computational weight and redundancy a possibility is to choose only part of the tiles – only chess ordered tiles, starting from the first tile (1,1) or from the second one (1,2) as well as taking into account only left sided or right sided tiles.

In our approach we split the images into $m \times n$ non-overlapping rectangles (tiles). The tiles are marked as (i, j), where $i \in 1...m$ and $j \in 1...n$. The index i increases from the left tile to the right tile and the index j increases from the top tile to the bottom tile of the image. From all pictures of the collection some of them are included into the learning set, the rest of the pictures remain in the testing set.

For each MPEG-7 descriptor $X \in \{SC, CL, CS, DC, EH, HT\}$ the algorithm consists of following steps:

- for all tiles of paintings feature vectors are calculated;
- the clustering procedure on the received vectors of the tiles from learning set is applied (the number of clusters is given as parameter);
- each cluster is named with serial number of clustering procedure;
- the tiles from the learning set receives corresponded labels that is the cluster name where they belong;
- the centroids of clusters are calculated;
- the tiles of the examining set receive the value of the examined feature equal to the cluster number of the closest centoid using L^1 metric.

As a result, each image is represented with a feature vector with $x \times m \times n$ attributes, where x is the number of MPEG-7 descriptors. For instance in case of using all MPEG-7 descriptors for 3×3 tiling, the number of attributes in this vector is $6 \times 3 \times 3 = 36$. In case of selecting only a subset of the available tiles (chess order or left/right side), the number of features reduces.

A specific of this approach is that received attributes are nominal. The main purpose of the prepared datasets after implementing this approach is to examine the significance of the attributes and the local/global trade-off for class prediction.

3.5 Other Attributes

The global features represent mean colour information about image. The pixels from each image (with dimensions $m \times n$) are transformed from RGB to HSL colour 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 colour psychology colour tones, lightness and saturation play important roles, and hence working in the HSL colour space, which is very near to human perceiving of the complex structure of the colour, 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 centre 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 centre rectangle when the image is split into 3×3 equal tiles but using HSL colour representation: *mean hue (centre):* $\frac{9}{m \times n}\sum_{i=m/3}^{2*m/3}\sum_{j=n/3}^{2*n/3} I_H(i,j)$, *mean saturation (centre):* $\frac{9}{m \times n}\sum_{i=m/3}^{2*m/3}\sum_{j=n/3}^{2*n/3} I_S(i,j)$, and *mean luminance (centre):* $\frac{9}{m \times n}\sum_{i=m/3}^{2*m/3}\sum_{j=n/3}^{2*n/3} I_L(i,j)$.

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 colour 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 $G(i,j) = \sqrt{\left(I_L(i,j) - I_L(i-1,j+1)\right)^2 + \left(I_L(i,j) - I_L(i+1,j-1)\right)^2}$ (for lighting the computations we use only diagonal differences).

4 APICAS: The System Description

The development of specialized digital libraries (DL) for art images has to combine the traditional DL functionality with specialized image processing tools. Such tools can be used at ingest of digitized art objects as a means to enhance their metadata in automated way, or for access if the users would like to benefit from content-based image retrieval (CBIR) or other semantic-oriented tools.

Here we are presenting architecture for a specialized art image DL which integrates general digital library functionality with designated CBIR tools. The suggested architecture had been implemented and the experience from this implementation informed this work.

4.1 Functional Requirements

The first step towards defining a suitable architecture for a CBIR system is to analyze the functional requirements it needs to meet. Our state-of the art review demonstrated that CBIR systems are developed most typically as specialized stand-alone applications or modules and are designed as such. This is a typical approach within an emerging domain but with the growing importance of image retrieval in the modern Web environment what becomes of special importance is how to develop modules for CBIR which could easily be integrated in digital repositories and web portals. This would require analysing functional requirements for CBIR systems in the context of functional requirements within the current trends in digital archives. In order to address them, we will first present the high-level architecture of modern digital archives.

In Chapter 1 of this book is presented international standard ISO 14721:2003 [1] Space data and information transfer systems – Open archival information system (OAIS) – Reference model [OAIS, 2002], which can be successfully implemented as common framework with concretizations for different digital collections of cultural heritage.

Within the context of such general digital archive architecture, CBIR-related implementations can be seen as a module which would best fit within the **Data Management** functional entity. However, it would also have influence on **Ingest** because the successful implementation of CBIR requires some specific data and metadata. CBIR also enriches the possibilities for delivery and will influence the **Access** functional entity which would accommodate more options for digital content discovery.

This wider context is reflected in the architecture of a CBIR system called "Art Painting Image Colour Aesthetics and Semantics" (APICAS); this system is fine-tuned to the need of Information Retrieval (IR) in the area of digitized art collections. The specialized core part of the system accommodated the necessary specific instrumentarium in terms of algorithms and methods for IR; these are seen as specialized instances of data management tools. At the same time the specific requirements for **Ingest** of specific data necessary for the IR components and the expanded **Access** possibilities are also highlighted.

[1] http://www.iso.org/iso/rss.xml?csnumber=24683&rss=detail

4.2 APICAS Architecture

The software system APICAS was developed in order to supply appropriate environment for testing several kinds of visual and higher level features, connected with the colour presence and interaction between colours within art images [Ivanova et al, 2008] [Ivanova and Stanchev, 2009] [Ivanova et al, 2010/ICDEM] [Ivanova et al, 2010/IJAS] [Ivanova et al, 2010/MCIS].

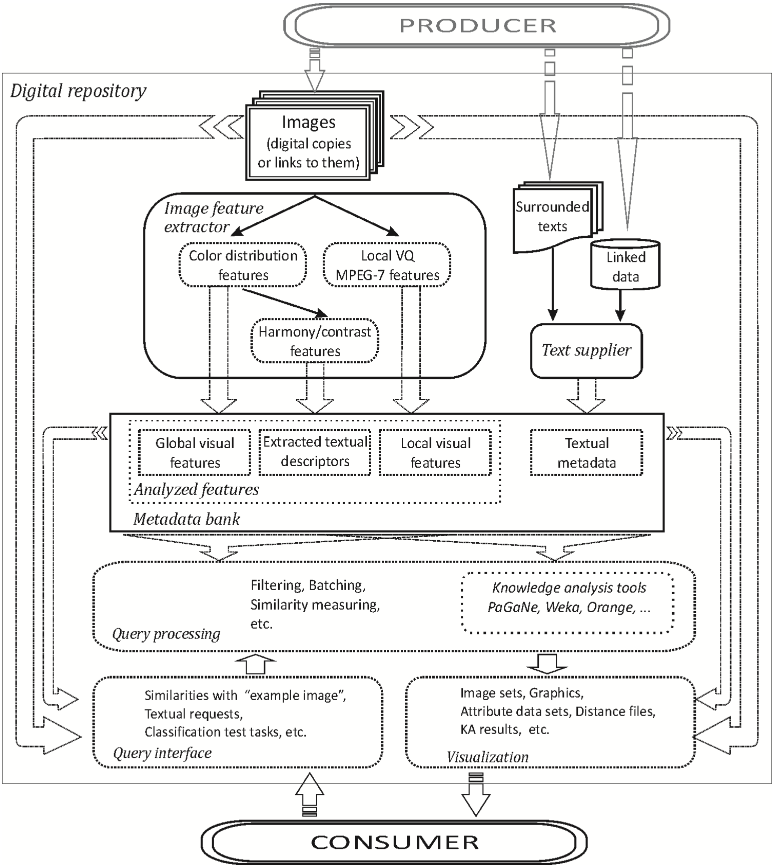


Figure 33. APICAS architecture

In Figure 33 the architecture of proposed system is shown. The functional schema of APICAS follows OAIS excluding functional entities on administration and preservation planning. The Ingest functions in such experimental system are also very simplified, because the focus is on the extracting of visual metadata and analysing received features.

The main functions in APICAS are:

- data entry – establishing connections with image sources as well as supplying controlling textual metadata;
- feature extraction – such functions produces automated metadata for image labelling;
- query interface – part of user-interface functions, connected with receiving of the tasks from the consumer. Here an image bank is used in order to select "an example" for searching images with greatest similarity to the selected image. The metadata bank is used for constructing a "controlled vocabulary", from which users can select desired feature(s);
- query processing – analysis of extracted metadata, their potential to meet user query for receiving images with specified colour harmonies or contrast or to be used for building artist practice profile or movement description;
- visualization – the other part of user-interface functions, connected with visualizing of received results. A variety of tools is used, such as image sets (whole images or patches), attribute data sets, distance files, graphics, knowledge analysis results, etc.

The main goals of APICAS are in two-fold:

- to analyse the possibilities of defined harmonies and contrast features for narrowing the semantic gap;
- to investigate possibilities for finding regularities between these features that can be used as semantic profile of the art paintings.

The analysis of the significance of the received characteristics and finding regularities between them can be used as discriminating semantic profile of the art paintings. It can predict several characteristics such as: the artists' names, movements, themes, techniques, etc. In this way the high level visual concepts, formed by combination of the features, can be used for narrowing the semantic gap between low-level automatic visual extraction and high-level human expression. We use data mining analysis environment PaGaNe [Mitov et al, 2009a] [Mitov et al, 2009b], developed in the Institute of Mathematics and Informatics, which supplied statistical and attribute analysing tools as well as specially designed Class-Association Rule classifier PGN.

4.3 APICAS Ground

The system is realized using CodeGear Delphi 2007 for Win32. As metadata storage space Arm 32, property of FOI Creative Ltd., is used. For obtaining the MPEG-7 descriptors APICAS refers to Multimedia Content Management System MILOS [Amato et al, 2004]. For obtaining the results of multidimensional scaling we used the open component-based data mining and machine learning software suite Orange [Demsar et al, 2004]. As clustering algorithm the program "vcluster", which is part of the CLUTO open source software package [Karypis, 2003] is implemented in the system. As knowledge analysis and testing environment, we used the data mining analysis environment PaGaNe [Mitov et al, 2009a] [Mitov et al, 2009b]. We use PGN classifier, ArmSquare association rule miner and implemented statistical analysing tools for checking up our results and extracting regularities for artists' and movements' styles based on the extracted attributes. As a control environment to the obtained results from the PGN classifier we used Waikato Environment for Knowledge Analysis (Weka) [Witten and Frank, 2005], developed at the University of Waikato, New Zealand.

4.4 APICAS Functionality

The system is built as an environment for carrying out different types of experiments. The starting screen connects several program modules, developed gradually over the years, in a common background.

Obtaining the colour distributions for further establishing colour harmonies/contrast descriptors may differ by used colour models or the way of calculating presence of dominant colours in the images:

- extracting colour distribution using exact quantization of the HSL-colour space [Ivanova et al, 2008];
- using MPEG-7 Dominant Colour descriptor as a source for determining colour distribution in the image and calculating of harmonies and contrasts features [Ivanova and Stanchev, 2009];
- using fuzzy calculations for establishing belonging of the colour characteristics into quantized bins [Ivanova et al, 2010/IJAS].

4.4.1 Functions that Serve Data Entry

➢ *Choosing the Collection*

The system operates with images in JPEG-format. Images, stored in one directory, form a collection. The user can choose the specific collection, changing the working folder (using a corresponded button). The system automatically scans new collections and forms a database.

There is a special button which allows rescanning and searching for the new images added in the collection.

- *Setting up Quantization Parameters and Boundaries*

A special screen allows changing the settings of some parameters and boundaries, concerning quantization of hue as well as of saturation or lightness (Figure 34). Access to user defined minimal thresholds, used in definition of different kinds of harmonies and contrast descriptors is also provided here.

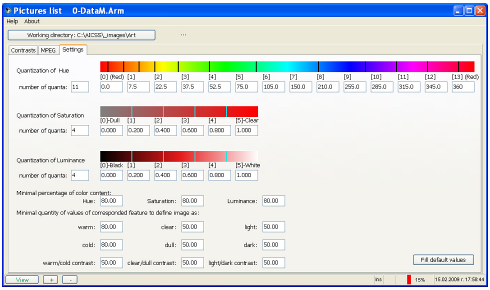


Figure 34. Screen for set up the quantization parameters and boundaries

- *Setting up Parameters for Vector Quantization*

The system allows flexible apparatus for defining parameters, used in the functions, which calculate local features, connected with vector quantization of MPEG-7 descriptors. These parameters are used also in the process of visualizing the results and forming the data for knowledge analysis. The user can choose which of the MPEG-7 descriptors to be included in the clustering procedure as well as in the process of preparing the datasets for knowledge analysis. The examined tiles can be given from the whole surface (LR), only from left (L) or right (R) half of the image. On the other side all tiles from a chosen surface can be given in chess-board order starting from the first tile (odd start) or from the second tile (even start). The last criterion is giving all elements, with or without tiles, which are at the boundary. The numbers of tiling by width and by height as well as the number of resulting clusters are given as parameters.

- *Selecting the Samples of Learning Set*

The files that contain samples of learning or examining set can be made manually (Figure 35). The names of these files are arbitrary, which allows keeping different variants of learning and examining set during the experimental process. The system APICAS facilitates the creation of these files by marking which image to be included in corresponded set. The paintings, which belong to the learning set or examining set, is extracted from selected by user file. The system check currently reading sample for availability in the current collection and marks them as participants of the learning set. In this way selected paintings can be fixed and used in different collections.

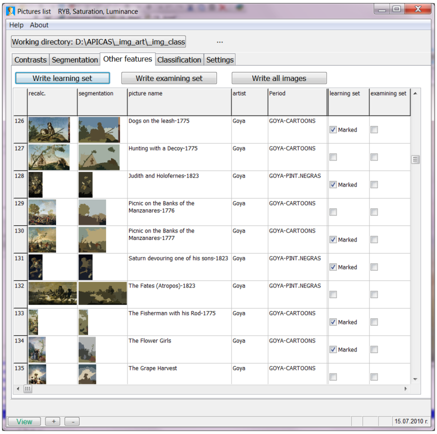


Figure 35. Grid, allowing manual selection of learning and examining set

4.4.2 Function for Supplying Textual Metadata

For the purposes of used learning algorithms as well as for testing received results the process needs of textual metadata, which describe different aspects of the image content. This information can be received by different ways – filled manually or derived from the context. In the Web space this information can be extracted from the Internet page, which contains examined image. This process taken alone is separate field for investigation. Here we use simple ways for supplying the process with needed metadata using the names of the images as a source for the names of the artist and the picture, and eventually – the year of painting. A simple ontology contains the information for the movements and sub-movements and artists. The ontology contains the connections between described concepts, which allow, using extracted from the filename information to receive all additional information that can be attached to the examined paintings. Other kinds of metadata, such as theme of the paintings, genre, used techniques, etc., can be added manually.

4.4.3 Functions for Calculating Visual Characteristics

➢ *Calculating Colour Distribution*

A special function calculates three dimensional array containing coefficients of participation of colours with correspondingly measured characteristics of the image. The function is used in the process of examining colour distribution as well as part of the process of defining harmonies and contrast descriptors. It gives each pixel from observed area, convert the colour value from RGB-colour model to colour coordinates in HSV or HSL colour model and as result of applying selected quantization increase the presence of colour with quantized coordinates. In the case of fuzzy quantization, the increasing catches neighbour coordinates with corresponded value. Finally the normalization of the values in the array is made. The output is three dimensional array which contain colour distribution by selected dimensions [Ivanova et al, 2008].

➢ *Estimating Harmonies' and Contrasts' Descriptors*

Special functions for calculating defined harmonies' and contrast' descriptors are realized in the system. The exact algorithms for estimating these descriptors are explained in [Ivanova and Stanchev, 2009] and [Ivanova et al, 2010].

➢ *Establishing Local Features, Based on Vector Quantization of MPEG-7 Descriptors over the Tiles of the Image*

This algorithm is presented in [Ivanova et al, 2009]. Several functions are connected with this process:

- choosing learning samples: the function reads text file that contains learning samples, check the images for existing in current collection, and writes correct samples in a database;
- clustering: this function passes into several steps: (1) creating tiles from images of the learning set with given parameters (numbers of tiles by width and by height); (2) calculating MPEG-7 descriptors for these tiles using MILOS system; (3) for each MPEG-7 descriptor building a dataset, which contains corresponding feature vector for each chosen tile from the learning set; (4) executing clustering procedure "vcluster" with selected number of clusters; (5) calculating the centroids of each cluster; (6) assigning the corresponded number for each tile and writing in a database;
- finding most similar tiles to the centroids: it is not used in the straight process of finding local features. It is connected with visualizing function of representatives of cluster values for corresponded MPEG-7

descriptor. The system finds the tile from the image base, which is closest to the centroids of examined descriptor;

- defining corresponded features for the rest of the images: for tiles of the images, which were not in the learning set, the membership of their centroids is calculated and the number of the corresponding cluster is assigned as a value of the tile. The result is written in the same way as for the images from the learning set.

For each MPEG-7 descriptor two types of similarity measures are realized: first is based on L_1-metric; second is based on L_2-metric, but for some of descriptors specific similarity measure can be used. For instance for *Scalable Colour* function takes into account the significance of the order of coefficients [Herrmann, 2002]. For *Edge Histogram* [Won et al, 2002] proposed one extension in order to capture not only the local edge distribution information but also semi-global and global ones.

➢ *Calculating Other Attributes*

The system is constructed as experimental environment, where different tools for extracting various attributes can be added. For instance, in [Ivanova et al, 2010/MCIS] was proposed other features (already discussed in previous point), their implementation in APICAS and their possible using for enforcing the power of metadata, connected with the paintings.

4.4.4 Functions, Connected with Output Information

➢ *Examining Colour Distribution*

One class of functions, realized in APICAS, is directed to carry out the analysis of distribution of colour characteristics in the images – hue, saturation or luminance, or combination of them (Figure 36). These functions are firstly introduced in [Ivanova et al, 2008], where the analysis is made on the base of HSL colour space. Further developments of these and additional features has shown that quantization of hue in respect of artists colour wheel is more appropriate, because of this additional possibility to make analyses based on constructed by us HSL-artist colour model is added.

The analysis can be conducted over the whole array (all three dimensions); a simple projection of selected characteristics; or projection of two characteristics (for instance, Hue and Luminance).

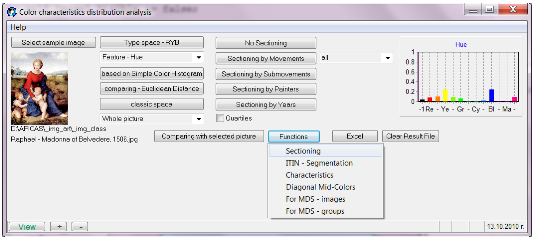


Figure 36. A part of the functions for colour characteristics distribution analysis

The functions can be executed over:

– all pictures in the collection;
– all movement or for a concrete movement, presented in the collection;
– all sub-movements or for a selected sub-movement;
– all artists or for a chosen artist in the collection.

The function selects and/or sections the images in the collection. For Obtaining colour distribution of a given image it refers to already discussed function for calculating colour distribution. If the calculations are already made, the function can overcome calculating the meaning values and only visualizes them using stored information. The result is displayed on the screen and in the same time is recorded as a "csv" file in the text directory of the system.

➢ *Visualizing Extracted Colour Harmonies and Contrast Features*

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 the extracted metadata, connected to this image – an example is given in Figure 37.

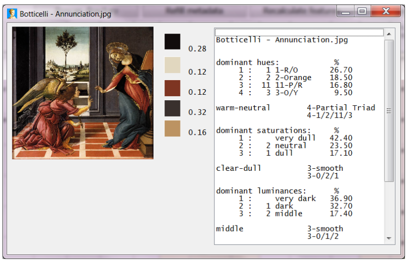


Figure 37. Harmonies/contrasts for the painting "Annunciation" by Botticelli

The user can set different conditions on the extracted descriptors and receive the images that satisfy these conditions. The results can be obtained in thumbnail form, where the images can be seen or in a file, where selected images can be additionally batched using other features, chosen by the user.

The system allows searching within a collection of images, which has specific combination of the colours, defined by some harmony or contrast. An example is shown in Figure 38.

Another branch of the system allows creating a datasets, containing extracted attributes or selected part of them labelled with chosen profile such as artist name, movement, scene-type. These datasets are 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 theme in the images.

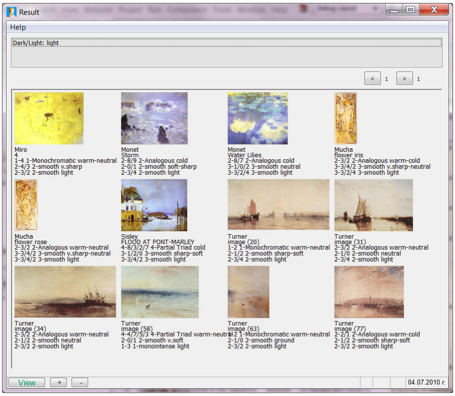


Figure 38. Result of retrieval from the image base with parameter:
"Dark/light contrast = Light" (includes "smooth light" and "monointense light")

➢ *Visualizing the Results of Clustering*

The system allows viewing of the results of clustering procedure showing all tiles, which belongs to selected number of cluster for specific MPEG-7 descriptor. For instance, in Figure 39 part of the tiles, which are in cluster No:2 of Colour Structure Descriptor for 5×5 tiling, is presented.

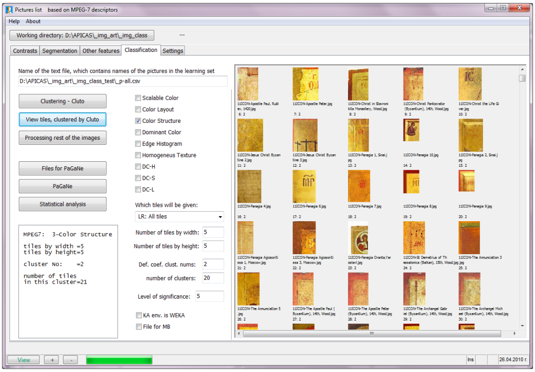


Figure 39. The screenshot of viewing 5×5 tiles, belonging to cluster No:2 of Colour Structure Descriptor

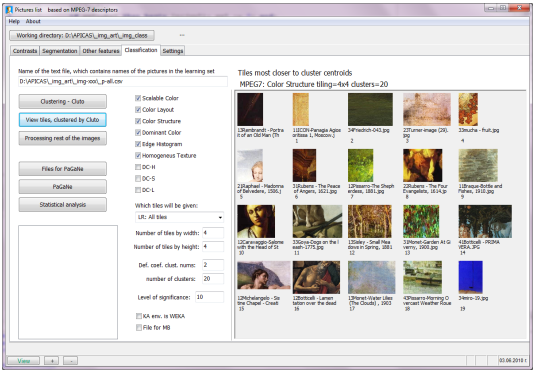


Figure 40. The tiles, most closer to the centroid of Colour Structure Descriptor (tiling 4×4 with 20 clusters)

Another function allows showing of the tiles from the learning set, which are closest to the centroids of given clustering for chosen MPEG-7 descriptor. The function uses the results of the already discussed function for finding most similar tiles to the centroids.

Figure 40 shows the tiles, closest to the centroid of Colour Structure Descriptor with tiling 4×4 and 20 clusters. The idea of this presentation is that these tiles can be used later as elements in a visual lexicon for representing specifics of some image profiles.

➢ *Preparing Data for Multidimensional Scaling*

The data for multidimensional scaling is prepared by special functions in corresponded rows. The distance matrices are calculated using Earth Mover Distance with special defining the distances of underlying data as follows:

✓ *For Colour Distribution Features*

If $I=(h_i,s_i,l_i)$ and $J=(h_j,s_j,l_j)$ are two points, where h_i and h_j are their hue values, s_i and s_j are their saturations, and l_i and l_j are their luminances.

The distance between I and J is calculated as Manhattan distance (L_1-metric) between distances of theirs characteristics: $d(I,J)=d_h(h_i,h_j)+d_s(s_i,s_j)+d_l(l_i,l_j)$.

Because of the angular type of hue characteristic, the distance is calculated as (Figure 41): $d_h(h_i,h_j)=\min(\left|h_i-h_j\right|, maxh-\left|h_i-h_j\right|)$.

For saturation and luminance distances the L_1-metric are used.

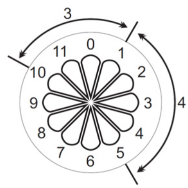


Figure 41. Angular distance

✓ *For Harmonies/Contrast Descriptors*

In spite of the categorical nature of these descriptors, their values can be partially ordered – for instance "Monochromatic" is closer to "Analogous" than to "Complementary". Special matrices that describe the distances between each two values of given descriptor are implemented.

✓ *For Local VQ MPEG-7 Features*

The resulting features of this process are strictly categorical and cannot be ordered in any manner. We use Jaccard coefficients as a ground for establishing similarity measures.

4.4.5 Preparing Data for Knowledge Analysis

Several functions for preparing datasets for further statistical and data analyses, which contain features calculated by proposed algorithms, are included into the system. The functions allow user to choose which of attributes to be included in dataset. As class label artist's name, movement, sub-movement, scene-type can be given. The results are prepared in different formats, convenient for PaGaNe, Weka or Orange.

An additional function allows creating dataset for associative rule miner ArmSquare, which makes frequency analysis over transactional datasets. The structure of the file differs from previous ones, which operate with rectangular datasets.

5 Experiments

For our experiments we have used datasets that include 600 paintings of 18 artists from different movements of West-European fine arts and one group, which represents Orthodox Iconographic Style from Eastern Medieval Culture. The paintings were chosen by an art expert reviewer. He has included in the collection the representative artists for the movements and most valuable paintings for each artist. We have used following movements and corresponded artists: *Icons*; *Renaissance* (Botticelli, Michelangelo, Raphael); *Baroque* (Caravaggio, Rembrandt, Rubens); *Romanticism* (Friedrich, Goya, Turner), *Impressionism* (Monet, Pissarro, Sisley), *Cubism* (Braque, Gris, Leger), and *Modern Art* (Klimt, Miro, Mucha).

5.1 Analysis of the Visual Features

Figure 42 shows the distributions of hues in the art painting images for examined movements. The predominate presence of warm colours (red-orange spectrum) in paintings are due to colouring of faces and bodies from one side and using the materials and varnish, which acquired yellowish tinge from other side. Not without importance is the fact that cold hues as blue and green are non-durable under the influence of light. On the other side technical artists practices of some movements did not use the green colour – this colour was replaced by brown. For instance, experiments of Constable at the beginning of XIX century to capture the inevitable light and shade effects of the nature with using more green colours was not accepted from their colleagues [Raychev, 2005].

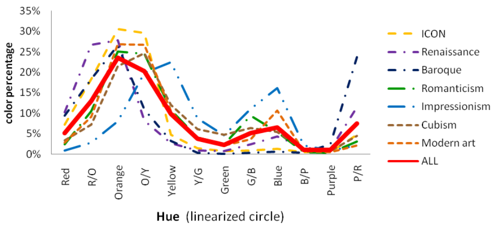


Figure 42. The Hue distribution of all pictures, grouped by movements

Figure 43 shows the distributions of saturation for each movement. The differences among these movements are obvious. The big difference of the global trend belongs to the Eastern iconographic style, which uses canonical representation of the figures with more schematic lines and pure colours (let's remember that values of saturation near 1 encode the pure colours).

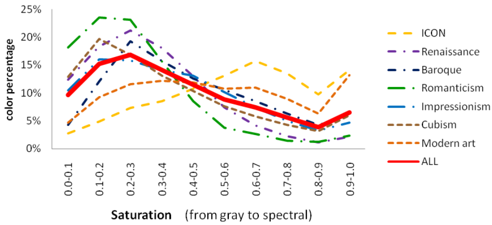


Figure 43. The Saturation distribution of all pictures, grouped by movements

Figure 44 shows the distributions of the luminance within groups determined by movements. Here Baroque highly differs with a big presence of dark colours (values of lightness near 0).

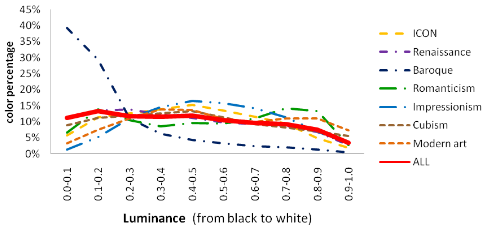


Figure 44. The Luminance distribution of all pictures, grouped by movements

From this unidimensional analysis we learn that distributions of the components are similar when grouped by movements. There is very specific luminance distribution for the Baroque movement, as well as the movement Icons has a specific saturation distribution.

APICAS allows making more complex analysis on combination of projections of the colour space. Some examples are given here. Analysis of the colour distribution on two projections – hue and luminance, has shown a predominance of dark orange colours in art paintings for Baroque. Similar predominance of warm colours, but in light tones is seen in Icons (Figure 45).

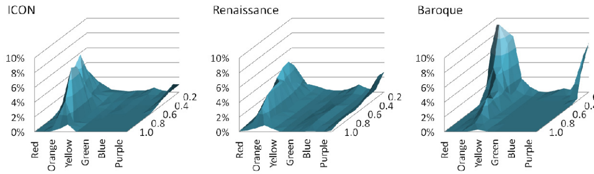


Figure 45. Hue-Luminance Distribution
for Icons, Renaissance and Baroque

In more contemporary movements, such as Romanticism, Impressionism, Cubism and Modern art, blue tonality has its strongest presence – lighter in Impressionism and darker in Modern art (Figure 46).

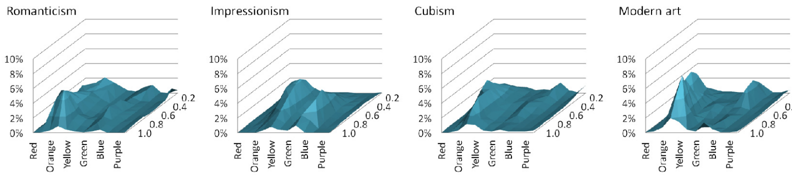
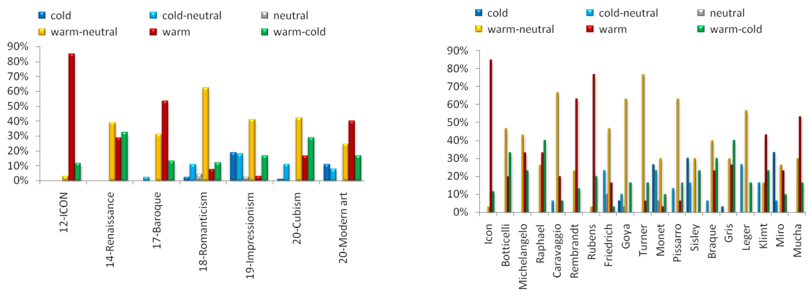


Figure 46. Hue-Luminance Distribution
for Romanticism, Impressionism, Cubism and Modern art

5.2 Analysis of the Harmonies/Contrast Descriptors

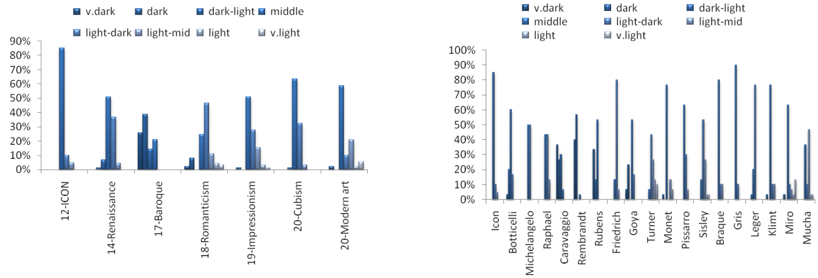
Some examples of distribution of defined harmonies and contrast descriptors by movements or artists styles are presented and explained by domain knowledge.



a) movements

b) artists' names

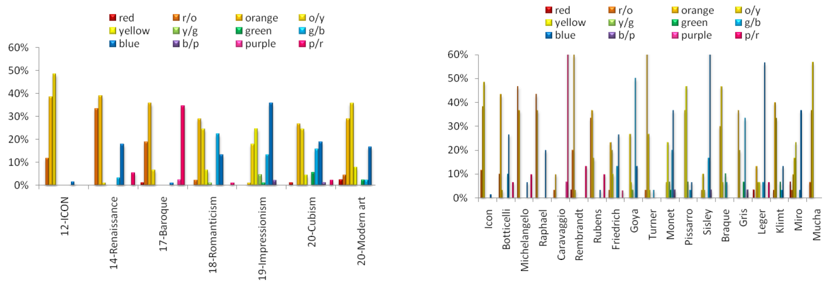
Figure 47. Distribution of paintings, based on cold/warm contrast.



a) movements

b) artists' names

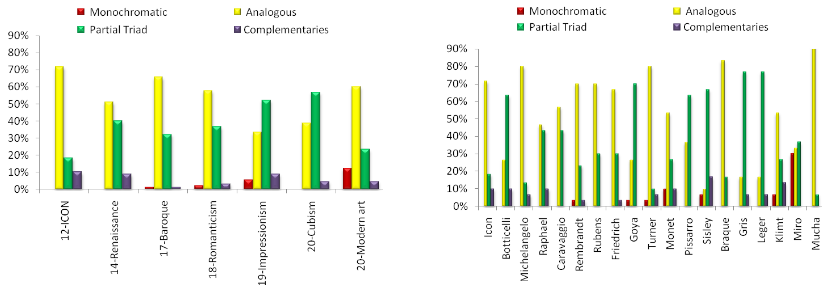
Figure 48. Distribution of paintings, based on light/dark contrast.



a) movements

b) artists' names

Figure 49. Distribution of paintings, based on first dominant hue



a) movements

b) artists' names

Figure 50. Percentage of different hue contrasts in the paintings

Figure 47 shows the distribution of images, 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 colour, which is main symbol of sacrificing and martyrdom. The big presence of dark warm colours 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 colour 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 [Itten, 1961].

Figure 48 shows the distribution of lightness in paintings from different movements and artists. The big presence of dark colours 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 [Raychev, 2005].

Figure 49 shows the distribution of images, based on the first dominant hue. As we have observed in our work [Ivanova et al, 2008] the colours around orange are frequently dominant colours in the paintings in classic art. More modern movements tend to use different colours as dominant.

Figure 50 shows the distribution of hue contrasts. As we can see partial triads are used in multiple cases of natural paintings, for instance Pissarro and Sisley. Instead of high abstractionism of Cubism such colour combinations are used often in the works of Gris and Leger. 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. [Koenig, 2010].

Generally we can say that there are some tendencies for using some colour combinations in different movements or artists.

5.3 Analysis of the Local Features

The first step is the development of a system that optimal uses the MPEG7 local features, extracted by proposed method (chapter 5), in respect of: the type of descriptors; position of tiles; number of clusters. MPEG-7 descriptors are complex descriptors. If we use these descriptors as described in chapter 5, we will obtain a vector with more than 300 attributes. Local features can capture more detailed information that can be useful for characterizing the artist's styles and movements, but it also introduces redundancy. This redundancy causes computational problems and can degenerate the results of the classifiers. The research challenge is to become local sensitive without significant loss of accuracy in the classification and retrieval tasks.

5.3.1 Evaluation Function for Significance of Attributes

We have processed the datasets under the procedures of attribute selection in order to receive the order of significance of attributes for prediction. We have implemented the Chi-square evaluation method. As datasets we have used 3×3 , 4×4 , 5×5 , 6×6 and 7×7 tiling and different numbers of clusters – 20, 40 and 60. As class value we have used "movements" and "artists' names". We have summarized the obtained order of attributes by different points of view – types of descriptors; positions of the tiles by width; positions of the tiles by height.

5.3.2 Selection of MPEG7 Descriptors

Figure 51 shows the distribution of significance of MPEG-7 descriptors for class prediction. As it is shown, the *Colour Structure* (*CS*) descriptor is the most informative for our datasets.

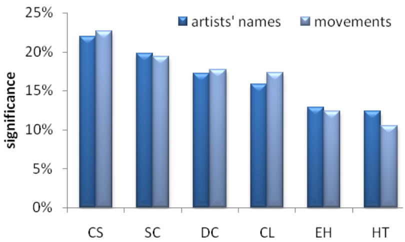


Figure 51. Average distribution of significance by MPEG-7 descriptors
over datasets, using different tiling and clustering, using Chi-square evaluation method

The dominance of the features based on the colour descriptors (CS, SC, DC, CL) leads to the following assumptions:

- The artist's palettes, which are captured in colour descriptors, are a powerful tool for creating the profiles of art painting images;
- Using this approach, texture descriptors (EH, HT) cannot produce sufficient quality attributes to present the specifics of the brushwork of the artists.

5.3.3 Optimize Spatial Granularity

We have made the analysis of the significance of the left/right side, respectively up/down part of the image. We have made from 3×3 to 7×7 tiling and average the results giving a half of centre tiles for odd tiling to participate on both parts.

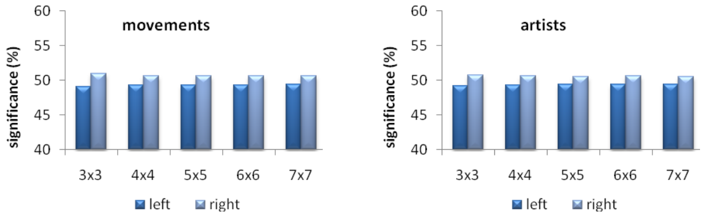


Figure 52. Distribution of significance
of left side and right side of the images with different tiling.

Figure 52 shows the distribution of significance of left side and right side of the images. The construction of many classical paintings is based on central symmetry. A little superiority of the right part of the image confirms the results from psychological theories for understanding human perception [Arnheim, 1974]. We intend to use this fact in further investigation with analyzing the tiles only of the right half of the image.

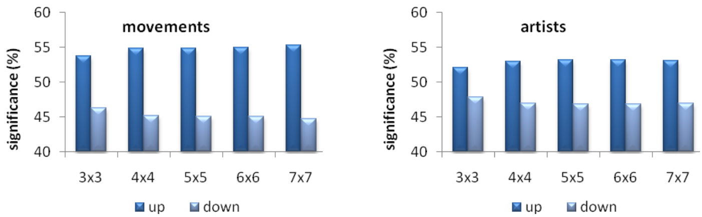
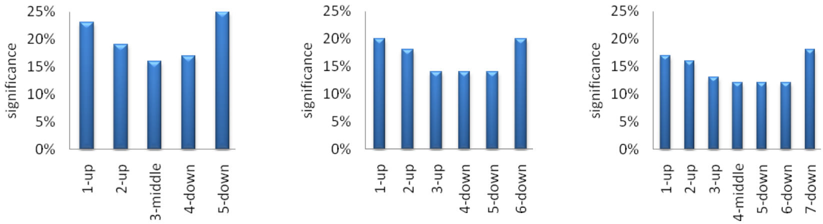


Figure 53. Distribution of significance
of upper and lower zone of the images with different tiling.

Figure 53 shows the distribution of significance of upper and lower zone of the images with different tiling. Based on these results we can conclude that upper part of the images is more informative than the lower one.



(a) $n = 5$ (b) $n = 6$ (c) $n = 7$

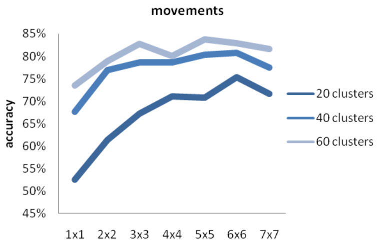
Figure 54. Distribution of significance of the tiles by position of height (up to down)

Similar analysis in respect to the vertical position of the tiles is shown on Figure 54. Here, it becomes clear that outer tiles (and especially border tiles) are more informative (more distinctive for different classes) than inner tiles (and especially centre tiles).

This fact can also be explained with differences in the composition in different styles [Arnheim, 1974]. While the central part of the image brings objects or scene information, the borders are less burdened with this task. In order to supply the focus of the image, there are not usually specific objects found here, but only the ground patterns, which are specific for the artists or the school, in which the artists belong. These patterns capture the ground of the artists' palette and brushwork.

Other experiments focused on establishing the appropriate number of clusters in order to receive good classification results with lower computational cost. We have run ten-fold cross-validation over the datasets.

The results displayed in Figure 55, show that using vector quantization on MPEG-7 descriptors for the entire image (i.e. 1×1 tiling) is not so informative. Better but non-sufficient results are obtained for 2×2 tiling. Tiling 3×3 is the first with relatively good results. This result is also conceptually validated by the fact that 3×3 tiling corresponds to a rough approximation of the golden ratio, which usually lies in the compositions of the art paintings. The last observed tiling 7×7 shows a decrease of accuracy, which can be explained by the fact that the pictures became too fragmented and the clusters fall not in the proper positions.



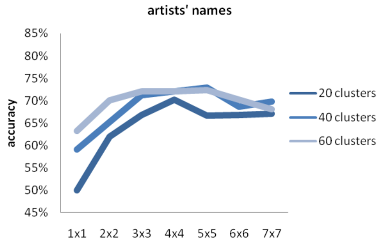


Figure 55. Classification accuracy for datasets
using 20, 40, 60 clusters and different numbers of tiling

6 Conclusion

A brief review of colour theory from different points of view, which became the basis for our study, was made. A brief historical overview of attempts to find colour interconnections and influencing the colours each other was given. Some colour models which are most suitable for representing the colours from human point of view were presented. An overview of already existing art image analysing systems and a study of the connection of the reviewed systems with the taxonomy of art image content had been made. Visual low-level features, which represent colour distribution in art images, were chosen as a ground for constructing higher-level concepts. The classification of harmonies and contrasts in accordance to Ittens' theory from the point of view of three main characteristics of the colour – hue, saturation and luminance, was made. The formal description of defined harmonies and contrasts was established. A method for extracting local features that capture local colour and texture information, based on tiling the image and applying vector quantization of MPEG-7 descriptors, calculated for the tiles of the image, has been described and implemented.

We have proposed architecture of an experimental CBIR lab-system, aimed analysing different types of visual features, which strive to narrow the semantic and abstraction gap between low-level automatic visual extraction and high-level human expression. We have explained the structure and functionality of the software system "Art Painting Image Colour Aesthetics and Semantics" (APICAS). All these functions we have realized and put into common environment APICAS. Experiments with realized features had been made.

The vividness of proposed features will open the door for indexing and searching in paintings repositories, according to such characteristics of their content. The proposed features can be used as a step 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.

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