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AN ANALYSIS OF COLOUR SEMANTICS IN ART IMAGES

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Abstract. The article briefly presents the results achieved by the PhD project R-1875 "Search in Art Image Collections Based on Colour Semantics", Hasselt University, which finished successfully. The main goals of this work were to provide a detailed analysis of the colour theories, especially on existing interconnections in successful colour combinations, as well as to formalize them in order to implement automated extraction from digitized artworks.

1. Introduction. The field of art image retrieval has to overcome a major challenge: it needs to accommodate the obvious difference between the digital technologies that are limited within pixels capture and human expectation

ACM Computing Classification System (1998): H.3.3; I.4.7.

Key words: Colour Theories, Content-based Image Retrieval, Metadata Extraction, Cultural Heritage.

*This article presents the principal results of the Ph.D. thesis A Novel Method for Content-Based Image Retrieval in Art Image Collections Utilizing Colour Semantics by Krassimira Ivanova (Institute of Mathematics and Informatics, BAS), successfully defended at Hasselt University in Belgium, Faculty of Science, on 15 November 2011.

for perceiving various semantic, aesthetic and cultural messages which the artwork sends to the viewer.

Colour perception underpins multiple aspects in art image analysis. They range from the physical nature of light to physiological specifics of the human vision system, psychological peculiarities and socio-cultural grounds in which the artwork was created, as well as these of the recipient of the message.

In the process of perception, figure-ground separation is the first cognitive step. Colour plays an important but secondary role. The colour responses are more connected to human emotions than to the rational mind. This property itself makes the colours' influence on human perception pivotal. The presence of one or more colours in different proportions conveys different messages, which can augment or suppress the perception of the observed objects. In the field of image retrieval the ways of perceiving colours and colour combinations as similar or dissimilar is crucial when one has to extract images based on a criterion reflecting the level of emotional perception, or to search for any specific characteristics of the artist's expressiveness.

The colour impact on people depends on multiple factors with physical laws and physiology being only the beginning. Further along this process of psychological perception plays an important role, with both the particular psychological state and the socio-cultural environment in which a character of a person is composed playing a role. Perception of colour brings up the whole emotional and mental identity of the artist as well as of the observer, joining their intelligence, memory, ideology, ethics, aesthetics and other sensations.

The main goals of the dissertation [1] were to provide a detailed analysis of the colour theories, especially on existing interconnections in successful colour combinations, as well as to formalize them in order to implement automated extraction from digitized artworks.

The article presents the proposed approaches for analysing colour semantics in art images. Section two draws attention to the phenomenon of colour interaction. Section three contains a theoretical description of the proposed approach. In Section four we discuss the experimental software system APICAS, which integrates the functions that retrieve the described features, and the tools for query answering and for making statistical and data mining analysis. Section five contains some experimental results. Finally, conclusions and future work are presented.

2. Colour Interactions and Influences. Johannes Itten [2] has given a very good formulation of the messages that one artwork sends to the viewer. He points out three basic directions of evincing colour aesthetics:

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

These characteristics are mutually connected and cannot live of full value alone: symbolism without visual accuracy and without emotional force would be merely an anaemic formalism; visually impressive effect without symbolic verity and emotional power would be a banal imitative naturalism; emotional effect without constructive symbolic content or visual strength would be limited to the plane of sentimental expression. Each artist works according to his temperament, and emphasizes one or another of these aspects [2].

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

Since Antiquity many scientists and artists have studied the phenomenon of colour interconnections:

- philosophers, such as Aristotle, who formulated questions about the difference of violet near white or black in "De meteorologica";
- artists, such as Leonardo da Vinci, who probably was the first to notice that when observed adjacently, colours influence each other;
- Isaac Newton (c. 1670), who dispersed light to its components from an electromagnetic point of view;
- Johann Heinrich Lambert and Ignaz Shiffermuller, who in parallel (1772) first presented colour pyramids and argued that three primary colours can construct all others;
- Philipp Otto Runge (1807), who looked from a chemical stance and made the first experiments with mixtures of colours in order to establish the primary ones;
- and many others.

So, from a physiological point of view, two main types of contrast can be discerned: simultaneous and successive contrasts.

- Simultaneous contrast argues that when colours interact, they are capable to change in appearance, depending on particular relationships with surrounding colours (initially suggested in 1839 by Michel Eugène Chevreul).
- Successive contrast means that the eye spontaneously generates the complementary colour even when the hue is absent (this explains the so-called afterimage phenomenon).
- These two types are based on the idea that "The human eye is satisfied (in equilibrium) only when the complementary colour relation is established".

Here is the time to mention the Bauhaus school in Weimar, where in the first half of the previous century Josef Albers, Adolf Hoelzel, and Johannes Itten developed their theories of successful colour combinations. They formalize similar basic types of harmonies and contrasts, used in art paintings.

Josef Albers (1888–1976) stated that one colour could have many "readings", depending on both lighting and the context in which it is placed. Colours interact and are modified in appearance by other colours in accordance with three guiding rules: (1) *Light/dark value contrast*; (2) *Complementary reaction*; (3) *Subtraction* [3].

Adolf Hoelzel (1853–1934) suggested seven contrast groups, based on his own understanding of the colour wheels, and each contrast marks some quality of colour perception: (1) *Contrast of the hue*; (2) *Light-Dark*; (3) *Cold-Warm*; (4) *Complementary*; (5) *Gloss-Mat*; (6) *Much-Little*; (7) *Colour-Achromatic* [4].

Johannes Itten (1888–1967) expanded the theories of Hoelzel and Albers. Through his research he also devised seven methodologies for coordinating colours utilizing the hue's contrasting properties: (1) *Contrast of hue*; (2) *Lightdark contrast*; (3) *Coldwarm contrast*; (4) *Complementary contrast*; (5) *Simultaneous contrast*; (6) *Contrast of saturation*; (7) *Contrast of proportion* [2].

Let's mention some examples of colour combinations used in artists' practice:

- the monochromatic and the analogous schemes are usually used to emphasize some visual unity – loneliness (e.g., in the paintings of Picasso's Blue period), quietness, joy, etc.;
- the variety of colours is used for influencing more complex associations, for instance as Itten said of Botticelli's painting "Lamentation over the Dead Christ": "The totality of hues symbolizes the cosmic significance of the epochal event";

– the strongest light–dark contrast is typical for Rembrandt's works. As Itten said, to Rembrandt colour becomes materialized light-energy, charged with tension when pure light colours often shine like jewels in dark surrounding;
– it is interesting that the two Cubists painters Gris and Braque applied totally different approaches to using saturation of colours – while Gris used relatively pure different colours, Braque's compositions are based mainly on gradient in saturation of one colour;
– the contrasts are often used in combination. For instance in van Gogh's painting "Cafe Terrace at Night" light–dark contrast is used in combination of the opposite hues yellow and blue.

3. Proposed Features.

We examine three types of colour features:

– visual features, which represent colour distribution in the images;
– global features that reflect colour harmonies and contrasts in art images;
– local features, based on vector quantization (VQ) of MPEG7 descriptors.

We use these features for:

– analysing the colour distribution in art images;
– searching the images by higher-level concepts, concerning harmonies and contrasts;
– analysing how more detailed information on semantic and abstraction content of art images based on MPEG7 descriptors with significant dimensionality reduction can be captured;
– classifying art images by different abstraction criteria, such as artists' names, periods or movements or semantic profile as genre of the art image.

3.1. Chosen Colour Model.

A colour model is an abstract mathematical model for describing the colour as a numerical vector, usually with three or four values, which are called colour components. Different models serve various domains – from physics and colorimetry, through painting, architecture, and design, to digital coding for printers, monitors and TV. History and practice show that a perfect colour model cannot be created: one is suitable to supplying compact coding and transmitting colour characteristics, another is easily perceived by humans, etc. From a human point of view, it is easiest to define colour as a composition of three components – hue, saturation and lightness. Hue means the name of the colour – red, orange, etc. Black, different shades of gray and white are called achromatic. Saturation measures the hue intensity or brilliance of a sample, its dullness or vividness. Lightness refers to relative light and dark in a sample [5]. Such a view on colour facilitates the structuring of colour contrasts and harmonies are evinced in art images. Even in the light of these three colour components there are several colour models, which have strengths and weaknesses.

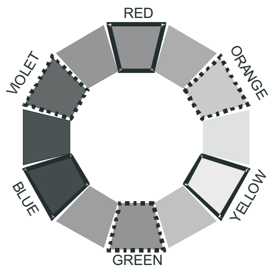


Fig. 1. The Artists' Colour Wheel

After analysis we decided to use one colour model that combines the advantages of three others: (1) RYB (Red-Yellow-Blue) model, adopted by artists, in whose colour wheel green stands opposite to red (Figure 1); (2) HSL (Hue-Saturation-Lightness); and (3) YCbCr, which very accurately represents brightness. We named this model "HSL-artists colour model". In this model:

- Hue (H) is based on the definition of Hue in the HSL colour model. But later, when we use quantization of Hue, we take into account the misplacement of the artists' colour wheel;
- Saturation (S) is the same as in HSL;
- Luminance (L) is obtained by the formula for the Luma component from YCbCr model.

If $R, G, B \in [0, 255]$ are the red, green and blue coordinates in RGB model:

$$max = \max(R, \max(G, B)), \quad min = \min(R, \min(G, B))$$

$$H = \begin{cases} 0 & \text{if } max = min \\ \left(60^\circ \times \dfrac{G - B}{max - min} + 360^\circ\right) \bmod 360^\circ & \text{if } max = R \\ 60^\circ \times \dfrac{B - R}{max - min} + 120^\circ & \text{if } max = G \\ 60^\circ \times \dfrac{R - G}{max - min} + 240^\circ & \text{if } max = B \end{cases}$$

$$S = \begin{cases} 0 & \text{if } max = min \\ \dfrac{max - min}{max + min} & \text{if } max + min \leq 1/2 \\ \dfrac{max - min}{2 - (max + min)} & \text{if } max + min > 1/2 \end{cases}$$

$$L = \frac{0.299 * R + 0.587 * G + 0.114 * B}{255}.$$

3.2. Visual Colour Distribution Features. Colour histograms are used as an approximation of an underlying continuous distribution of colours' values [6]. The pixels in the images are converted into the HSL-artist colour model. The quantization of Hue is made to 13-bins, $ih = -1, \ldots, NH - 1$, $NH = 12$, where one value is used for achromatic colours ($ih = -1$) and twelve hues are used for fundamental colours ($ih = 0, \ldots, NH - 1$). The quantization function is non-linear with respect to taking into account the misplacement of the artists' colour wheel and Hue definition in HSL colour space. The quantization intervals are given in Figure 2.

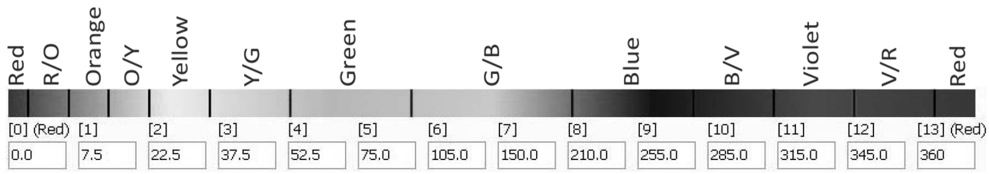


Fig. 2. Quantization of Hue

The saturation and lightness are linearly quantized into NS-bins ($is = 0, \ldots, NS - 1$), respectively NL-bins ($il = 0, \ldots, NL - 1$).

Because the number of bins is relatively small, to refine colour distribution we use a fuzzy function for calculating the quantization part of the colour characteristic (Figure 3).

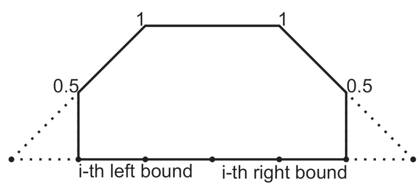


Fig. 3. Quantization part of colour characteristic

As a result, every picture is represented with a three-dimensional array containing coefficients of participation of colours with correspondingly measured characteristics of the picture: $A = \{A(ih, is, il) | ih = -1, \ldots, NH - 1;\ is = 0, \ldots, NS - 1;\ il = 0, \ldots, NL - 1\}$.

An analysis of colour distribution can be made on three directions together or only on two or one of them.

3.3. Harmonies and Contrast Descriptors. We examined the following harmonies and contrasts:

- harmonies/contrasts based on the disposition of hues – they are defined as a relative disposition of hues on the colour wheel. Here are examined monotone compositions, analogous hues, complementary contrasts, triads, tetrads, and some variations of them;
- cold/warm contrast, which is based on the absolute meaning of colour;
- clear/dull combinations;
- light/dark combinations.

For defining hue harmonies/contrasts we use the hue projection of a three-dimensional array. On its base the so-called hue order vector, which contains the number of dominant hues nh, and positions of dominant hues, ordered in decreasing percentage, is constructed. Additionally, the Boolean functions that confirm presence of some relative disposition of one colour against the colour p are defined: opposite to p; left neighbour of p; right neighbour of p; element of the triad at the left side of p; element of the triad at the right side of p; element of the tetrad at the left side of p; element of the tetrad at the right side of p. The hue harmonies/contrasts are defined as combinations of these functions. Later, we examine the fulfilment of these combinations using as arguments the colours indicated by the hue order vector.

Unlike hue, which is circular and continuous, saturation and lightness are linear. That difference makes for different definitions of harmonies/contrasts for these characteristics. For harmonies/contrasts from saturation and luminance point of view again corresponded order vector is constructed. Depending on how many values and which ones exceed some boundary, different situations can be examined – monointense, contrary, or smooth.

From the saturation point of view the picture can contain saturated or unsaturated colours or a combination of them.

From the luminance point of view the global tone of the images can be very dark, dark, middle, light, very light, or a contrasting combination of them.

Especially for cold/warm contrast we use the whole array because the “temperature” of the colour depends not only on the hue (red-orange is the warmest and blue-green is the coolest), but also on the saturation and luminance (for instance: increasing the lightness in unsaturated colours leads to an increasing of coldness and increasing the lightness of saturated colours cause expanding of both families of warm and cold colours).

The comprehensive definitions of these descriptors are given in [7] and [1].

3.4. Local VQ MPEG-7 Descriptors. The third group of descriptors are based on a vector quantization of MPEG-7 descriptors over the partitioned images [8]. They are used to analyse the possibilities of capturing more detailed information on the semantic and abstraction content of art images. MPEG-7 descriptors are complex descriptors, which provide a good presentation of different types of visual features [9]. These complex structures need specific processing and cannot be properly interpreted by generic classification algorithms. In our work we focus on the following MPEG-7 descriptors: Scalable Colour (SC); Colour Layout (CL); Colour Structure (CS); Dominant Colour (DC); Edge Histogram (EH); Homogeneous Texture (HT), which are used for describing the image content. Vector quantisation is used as a tool for dimensionality reduction.

In our approach we split the images into $m \times n$ non-overlapping rectangles (tiles). The tiles are marked as (i, j), where $i \in 1, \ldots, m$ and $j \in 1, \ldots, n$. 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. Some of the pictures of the collection are included into the learning set, the rest of the pictures remain in the testing set.

For each MPEG7 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 is applied on the vectors received from the tiles of the learning set (the number of clusters is given as parameter);

– each cluster is named with the serial number of clustering procedure;

the tiles from the learning set receives labels corresponding to 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 by a feature vector with $x \times m \times n$ attributes, where x is the number of MPEG7 descriptors. A specific feature of this approach is that the obtained 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.

4. The APICAS System. In order to establish an environment for testing the proposed features we developed the experimental system APICAS – an acronym from "Art Painting Image Colour Aesthetics and Semantics".

The main system functions can be categorized into the following groups:

- data entry – establishing connections with image sources as well as supplying controlling textual metadata;
- feature extraction – such functions produce automated metadata for image labelling;
- query interface – part of the user-interface functions, connected with receiving 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 match the user query for receiving images with specified colour harmonies or contrast or to be used for building an artist practice profile or movement description;
- visualization – the other part of the user-interface functions, connected with visualizing the 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 system is realized using CodeGear Delphi 2007 for Win32. As metadata the storage space Arm 32, property of FOI Creative Ltd., is used. For obtaining the MPEG7 descriptors APICAS refers to the Multimedia Content Management System MILOS [10]. For obtaining the results of multidimensional scaling we used the open component-based data mining and machine learning software suite ORANGE [11]. As clustering algorithm the program "vcluster", which is part of the CLUTO open source software package [12], is implemented in the system. As a knowledge analysis and testing environment, we used the data mining analysis environment PaGaNe [13][14] and Waikato Environment for Knowledge Analysis (WEKA) [15].

5. Experimental Results. The datasets we used for our experiments include 600 paintings by 18 artists from different movements of West European fine arts – Botticelli, Michelangelo, Raphael (Renaissance); Caravaggio, Rembrandt, Rubens (Baroque); Friedrich, Goya, Turner (Romanticism); Monet, Pissarro, Sisley (Impressionism); Braque, Gris, Leger (Cubism); Klimt, Miro, Mucha (Modern Art); and one group which represents the Iconographical Style of the Eastern medieval culture. In order to simplify the statistical processing we used an equal number of paintings by each artist; only the group of Icons was twice the size of other sets.

For the predictive analysis we use the classifiers OneR, JRip, J48 and PGN, which are representatives of different classification schemes (Decision Rules, Decision Trees, Associative Classifiers), but all create rules, or can be written as rules, on whose base the recognition process is made. The experiments are made using 5-fold cross-validation and applying Chimerge discretization with 95% significance level for numerical attributes.

The results of the descriptive analysis are compared with the domain knowledge. For the predictive analysis we use classical hold-out measures such as accuracy for classification and recall and precision for retrieval.

5.1. Analysis of the Colour Distribution.

Descriptive Analysis. The descriptive analysis of the colour distribution of one projection revealed some general trends for pictures that we used as a normalizing factor in determining harmonies/contrast descriptors. On the other hand, it showed some specific characteristics of the periods which have an explanation of technical or socio-cultural character.

For instance, the predominant presence of warm colours (red-orange spectrum) in paintings are due to the colouring of faces and bodies on one side, and using materials and varnish which acquired a yellowish tinge on the other side. Not without importance is the fact that cold hues such as blue and green are non-durable under the influence of light. On the other hand, the technical artists' practices of some movements did not use the colour green – this colour was replaced by brown. For instance, the experiments by Constable at the beginning of the 19^{th} century to capture the inevitable light and shade effects of nature by using more green colours were not accepted by their colleagues [16]. From a saturation point of view the most distinctive is the Eastern iconographic style, which uses canonical representation of the figures with more schematic lines and pure colours. Some common trends for most movements concerning luminance are also seen. Only Baroque is considerably different with the big presence of dark and very dark colours.

The descriptive analysis of two projections (in this case hue and lightness) shows that the periods are relatively divided into two big groups – classical and contemporary – with warmer tones in classic paintings and the presence of cold in contemporary paintings with variations in brightness in the different movements (Figure 4 and Figure 5).

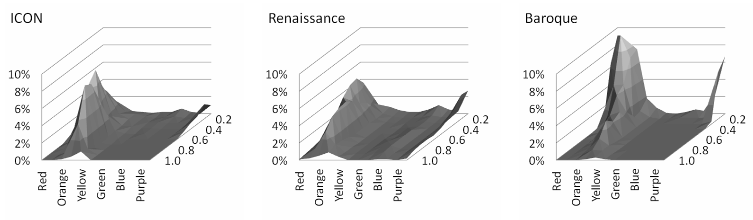


Fig. 4. Hue-Luminance Distribution for Icons, Renaissance and Baroque

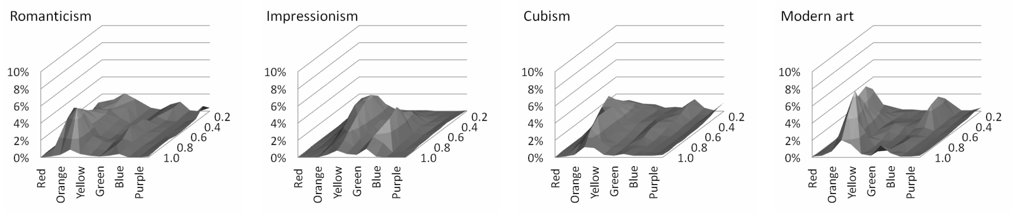


Fig. 5. Hue-Luminance Distribution for Romanticism, Impressionism, Cubism and Modern art

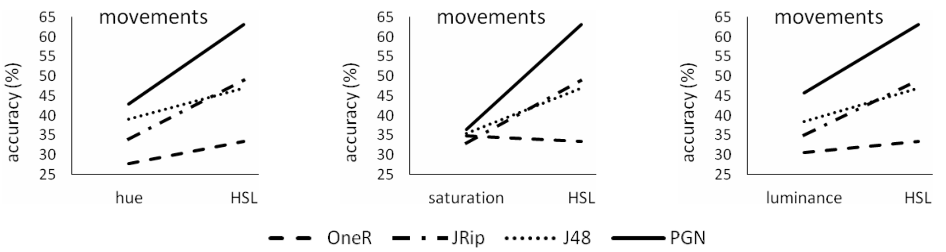


Fig. 6. The accuracies of different classifiers by hue, saturation, luminance separately and all three together

Predictive Analysis. We made a three-fold cross validation using the datasets that contains hue values, saturation values, luminance values separately and all three together [17].

We compared the accuracy of the classifiers: OneR, JRip, J48, and PGN (Figure 6). PGN shows the highest accuracy among the examined models for all datasets. PGN showed the greatest increase in accuracy when considering the three characteristics together, which confirms that the associative classifiers (in particular PGN) have the best opportunity for the extraction of specific combinations of attribute values.

5.2. Analysis of the Harmonies/contrast Descriptors. This group of experiments was focused on the analysis of the automatic annotation of images with harmonies/contrast descriptors. These high-level characteristics can be used in the processes of categorization in order to uncover cultural influences and specific techniques, as well as for recourse discovery with given characteristics closely associated with emotional reactions caused by the images. These characteristics relate to the elements of the abstract space of the image content.

Descriptive Analysis. The analysis of the use of different contrasts of hue in the pictures showed that very often partial triads are found in the landscapes (Pissarro, Sisley). Despite the high abstractionism of Cubism, partial triads have also been seen (Gris, Leger). Triads are often used in Botticelli and Goya's paintings, as an exponent of the complexity of the composition. Paintings with monochromatic and analogous harmonies contain other expressive techniques, e.g., light/dark contrast in Baroque, saturation gradient in Cubism (especially in Braque's style), etc.

The distribution of images based on cold/warm contrast also shows some trends: 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 as a symbol of sacrifice and martyrdom. The big presence of dark warm colours is specific for Baroque. Presenting nature in paintings is typical for Romanticism, which leads to strengthening the presence of cold (green and blue) tones. This tendency increases in Impressionism. Intensive study of nature led the Impressionists to an entirely new colour rendition. The study of sunlight, which alters the local tones of natural objects, and of light in the atmospheric world of landscape, provided the Impressionist painters with new essential patterns [2].

The distribution of light/dark combinations in paintings also has certain tendencies that have their explanation in technical and psychological aspects. For example, the use of dark tones and dark–light contrast in Baroque is linked to the search for maximum expressiveness on the one hand and with the practice of painting by candlelight in the studio on the other hand [16]. Also, the special attention to studying the capture of light in the Impressionists' paintings was facilitated by the very practical fact that the chemical factories started production of paints in tubes and artists had the opportunity to go outdoors.

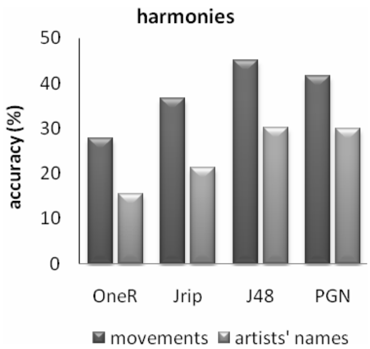


Fig. 7. Accuracy of different classifiers – based on harmonies/contrast descriptors

Predictive Analysis. The harmonies/contrast features try to extract very global colour combination constructs. Because of this we do not expect that such features can be used for exact classification of movements or artists. We put these descriptors into the classification task in order to see whether there are any tendencies.

Figure 7 shows the accuracies of different classifiers, based on harmonies/ contrast descriptors with movements and artists' names as class labels. Taking into account the facts that the features are too global and the numbers of class labels are great, we obtain acceptable results. Here the best classification model is J48 following by PGN.

Figure 8 and Figure 9 present the visualization of the corresponding confusion matrices. Here, the darkness intensity corresponds to the percentage of queries, which are actually of the class label indicated by the row and were predicted as the class label indicated by the column. The more detailed analyses showed that in this case the rule-based classifiers OneR and JRip do not produce good classification models, creating rules that overuse Renaissance in the case of movements, as well as Icons in the case of artists' names. OneR and JRip take

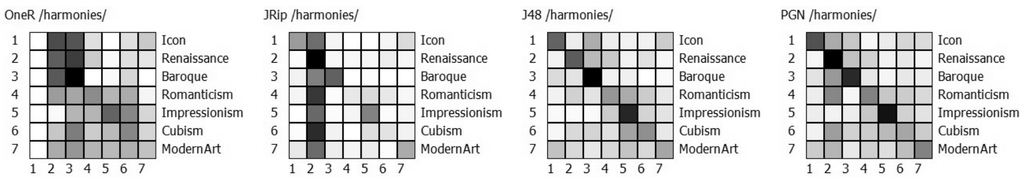


Fig. 8. Confusion matrices for harmonies/contrast features, movements as class labels

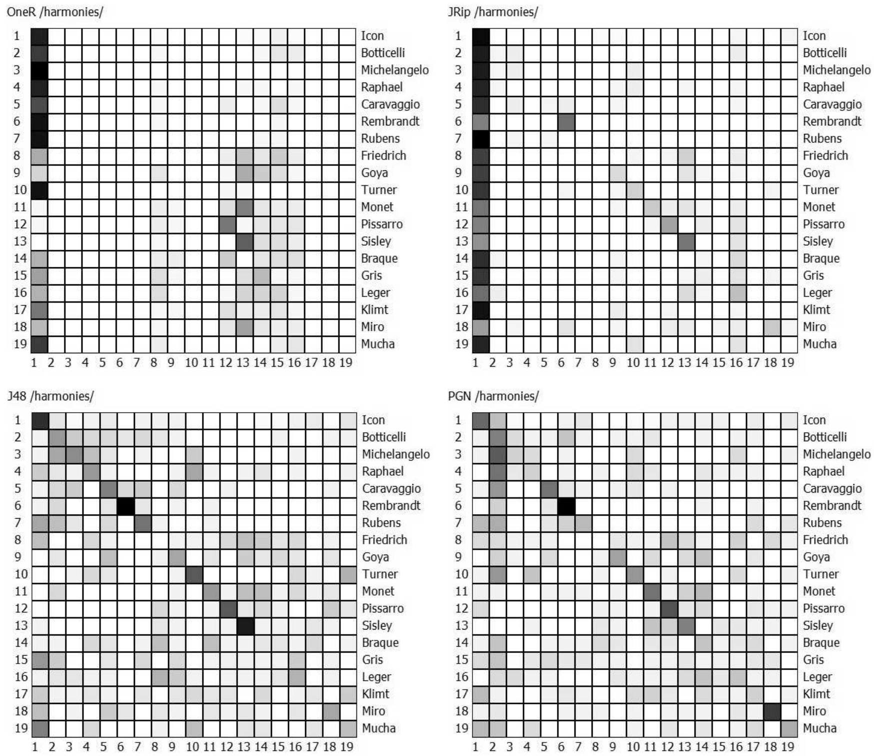


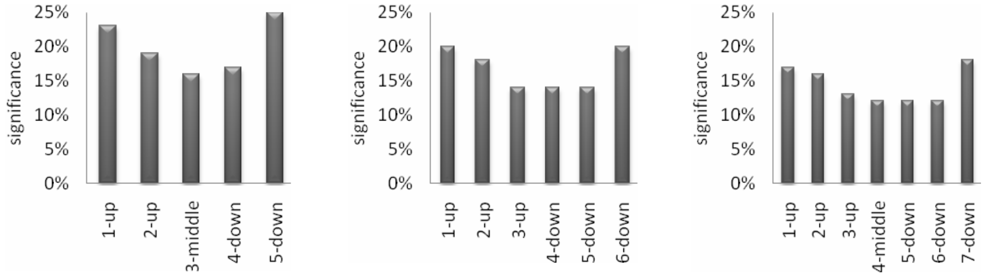
Fig. 9. Confusion matrices for harmonies/contrast features, artists' names as class labels

into account the support that leads to false prevailing Icons in the case of artists' names where the Icon pictures are two times more than those from other classes, contrary to PGN, which focuses primarily on the confidence of the association rules and only at a later stage on the support of the rules.

5.3. Analysis of the Local VQ MPEG-7 Descriptors.

Descriptive Analysis. With local features we try to capture more detailed information on the significance of a particular image part.

An analysis of the distribution of significance on the left side and the right side of the images shows that both sides have relatively equal importance. This can be explained by the fact that the construction of many classical paintings is based on central symmetry of the concept disposition. A little superiority of the right part of the image confirms the results from psychological theories for understanding human perception [19].



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

Fig. 10. Distribution of significance of the tiles by position of height, $j \in 1, \ldots, n$ (up to down)

The analysis of the distribution of significance of the upper and lower zone of the paintings (Figure 10) shows that the upper part of the images is more informative than the lower one. Additionally, the outer tiles (and especially border tiles) are more informative (more distinctive for different classes) than the inner tiles (and especially centre tiles).

This fact can also be explained with differences in the composition in different styles [19]. 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, usually no specific objects are found here, but only the ground patterns, which are characteristic of the artists or the school to which the artists belong. These patterns capture the ground of the artists' palette and brushwork.

Predictive Analysis. The group of experiments for evaluating the accuracy of the classification by the examined classifiers confirmed the hypothesis that the PGN classifier has good performance. This enables the use of rules produced by the classifier PGN, as a profile of a class, period, artist, genre, etc.

Figure 11 shows the confusion matrix of the PGN classifier for artists' names, with marks of the movements' groups. It is seen that local misclassifying within the frame of movements happens mainly for Renaissance and to some extent for Impressionism and Cubism; this confirms the proposition about similar features existing in the movements.

The scatterplot of F-measures of PGN against other classifiers (Figure 12) shows that PGN has not only the best accuracy, but also better local behaviour within class labels – most of the F-measures are in the upper zone of the graphics. This confirms our expectation that PGN would be well suited to predicting multi-class datasets.

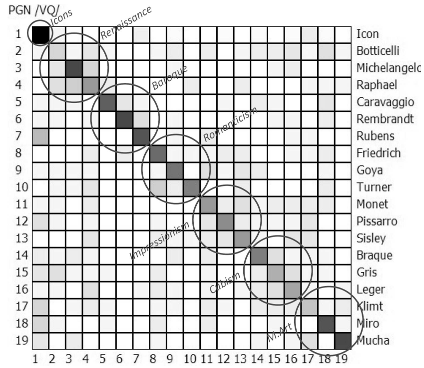


Fig. 11. Visualisation of the confusion matrix of PGN for VQ-MPEG7 descriptors, artists' names as class label with grouping by movements.

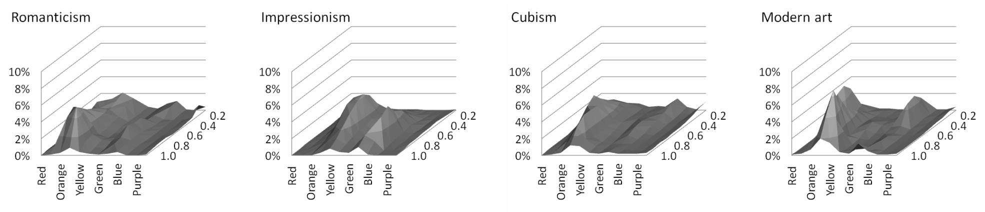


Fig. 12. Scatterplots of F-measure of PGN against other classifiers for VQ-MPEG7

6. Conclusion and Future Plans. We propose a colour model appropriate for extracting contrast characteristics constructed as a combination of three other models. The model is easily comprehensible while also allowing for efficient conversion from RGB.

On the basis of this model we elaborate a formal description of harmonies and contrasts from the point of view of three main characteristics of the colour – hue, saturation and luminance.

We also offer an experimental CBIR system architecture as an environment for applying the proposed algorithms.

The implemented system "Art Painting Image Colour Aesthetics and Semantics" (APICAS) is used for conducting a series of experiments, such as:

- similarity search with a selected image by one or more of the extracted features;
- search of images that satisfy user queries featuring contrasts' characteristics;
- investigation on the possibilities to integrate such characteristics within a specialized resource discovery.

Experiments were made to evaluate the features' added value. The descriptive analysis shows the common trends and specifics of examined feature projections. The predictive analysis with classification, especially tree classifiers and associative classifiers, shows the benefits of using such features within the recognition process of artists' styles, movements or groups of movements.

The plans for further research are focused on:

– analysing the possibilities of using SIFT-descriptors [20] as a ground for defining upper-layer concepts;
– focusing on the processes of throwing out redundant attributes in order to achieve clearer and faster results;
– applying already extracted as well as newly developed attributes and corresponding methods in the field of analysis of Eastern Iconographical painting schools (especially the Bulgarian tradition) and themes within the icons.

The growing number of digitised cultural heritage collections brought users' access to art collections to a radically new level. Accessibility, however, is hindered by the very large volume of available resources, which calls for new approaches in resource discovery building on methods for content based image analysis; this would enhance search using not only available metadata but also user preferences related to the image content.

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