A Novel Method for Content-Based Image Retrieval in Art Image Collections Utilizing Colour Semantics

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Outline of the phd thesis

1. Introduction
2. CBIR in Art Image Collections – the State of the Art
3. Real and Digitized Colour World
4. Some Examples of CBIR Systems
5. Proposed Set of Visual Attributes
6. The System APICAS
7. Experimental Results
8. Conclusions and future work

The Goals

The main goals of this work are:

- to provide a detailed analysis of the colour theories, especially on existing interconnections in successful colour combinations
- to formalize them in order to implement automated extraction from digitized artworks.

We use Itten's colour theory as a starting point.

Content Base Image Retrieval (CBIR)

CBIR is any technology that in principle helps to organize digital images based on their content.

CBIR has three components:

- Feature design - to make mathematical description of an image for the retrieval purposes as its signature
  - features: colour, texture, salient points, shape, spatial relations...
  - data reduction techniques: dimensionality, numerosity
- Indexing - organizing in a database
  - access methods
- Retrieval - the retrieval engines build the bridge between the internal space of the system and the user queries
  - similarity: numerical, categorical, of probabilities, or structures...

Art Image Content as Extracted by the Viewer

[Jaimes and Chang, in 2002]:

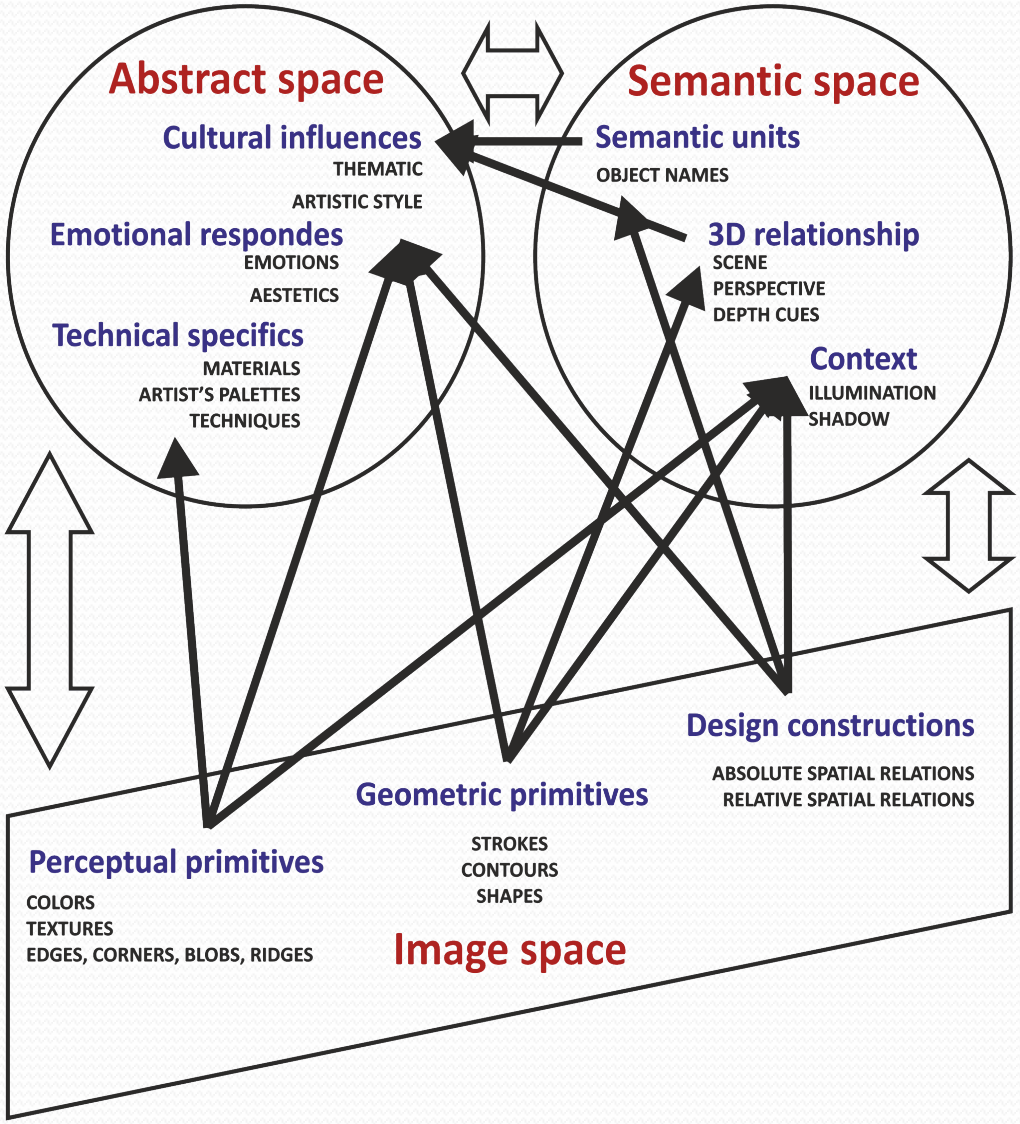
- Visual *percepts*
- Underlying abstract idea, which corresponds to *concepts*

Inspired by
[Burford , Briggs, Eakins, 2003] and
[Hurtut, 2010]:

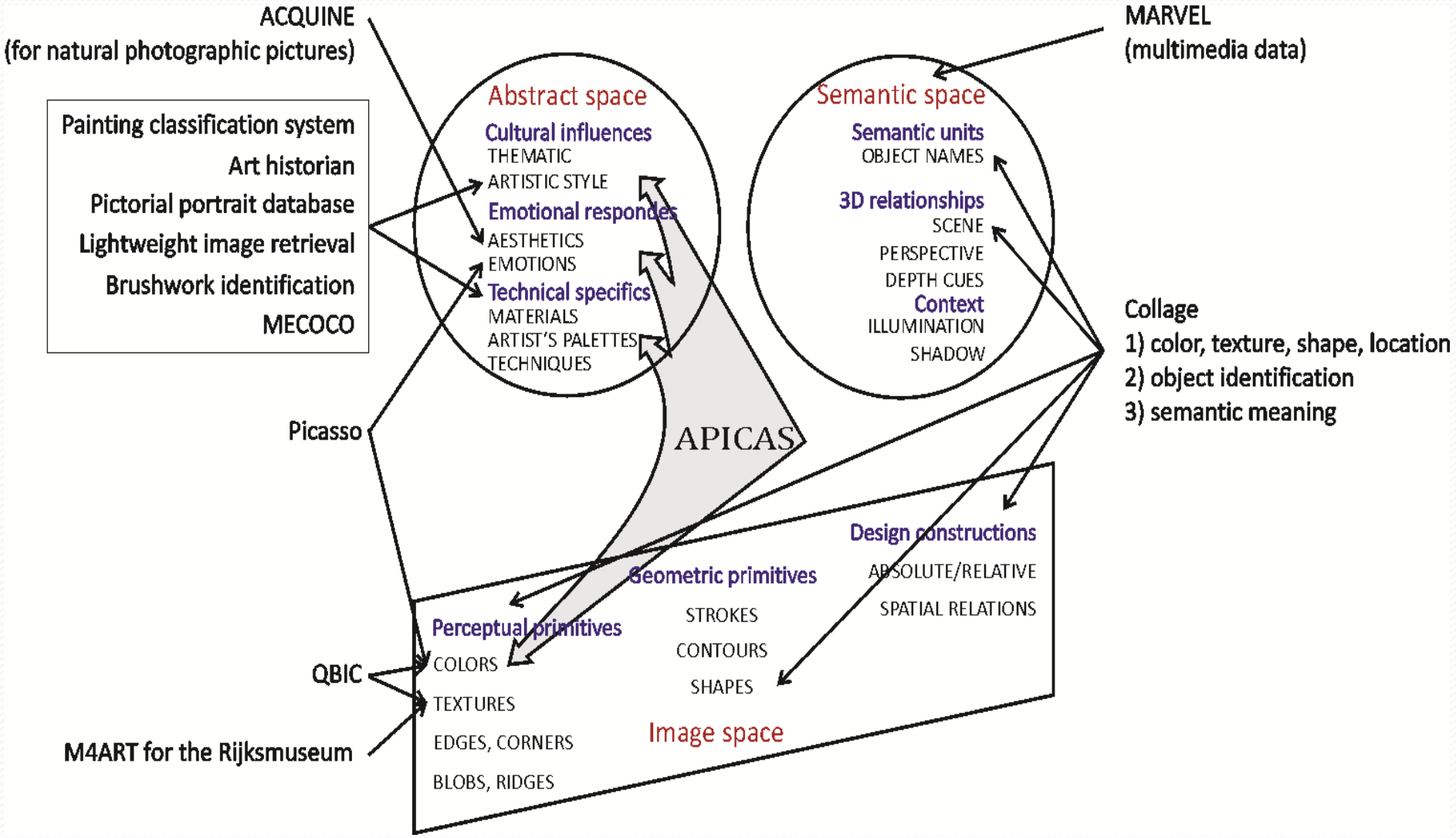
Image space contains visual primitives, needed to record an image through visual perception.

Semantic space is related to the meaning of the elements, their potential for semantic interpretation.

Abstract space reflects cultural influences, specific techniques, and emotional responses.



Art Image Content



Harmonies and Contrasts

Aristotle, da Vinci (1510), Newton (1666), Lambert, Schiffermüller (1772), Runge (1807), ... , Seurat (1886), ...

From physiological point of view:

- Simultaneous contrast: when colours interact, they are capable of change in appearance, depending on particular relationships with surrounding colours (1839 - Michel Eugène Chevreul)
- Successive contrast: the eye spontaneously generates the complementary colour even when the hue is absent (afterimage phenomenon)

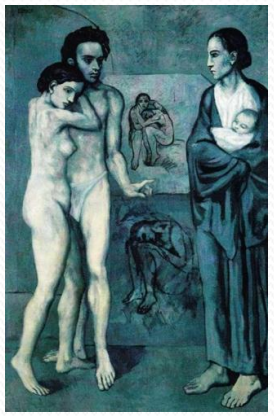
Successive and simultaneous contrasts suggest that **the human eye is satisfied (in equilibrium) only when the complementary colour relation is established.**

- Adolf Hoelzel (1853-1934) :
  - Contrast of the Hue;
  - Light-Dark;
  - Cold-Warm;
  - Complementary;
  - Gloss-Mat;
  - Much-Little;
  - Colour-Achromatic .
- Johannes Itten (1888-1967) :
  - Contrast of hue;
  - Light-dark contrast;
  - Cold-warm contrast;
  - Complementary contrast;
  - Simultaneous contrast;
  - Contrast of saturation;
  - Contrast of extension.

Examples - Hue Harmony

"*Picasso's blue period was characterized by his dominant use of a monochromatic blue color scheme to enhance the melancholy subjects of the paintings*" [Koenig, 2010]

Picasso: The Tragedy (1903)
Monochromatic



Picasso: La Vie (1903)
Monochromatic

Monet: Ice Floes Misty Morning, 1894
Analogous: blue / blue-green

Monochromatic and analogous schemes are very harmonious and emphasize visual unity.

Picasso: The Girl with a Goat (1906)
Analogous: yellow/orange

Examples - Hue Contrasts

Theotokos of the Passion (13th-15th c.)
Contrast of Hue is often used in Icons

Botticelli: Lamentation over the Dead Christ (1490-1492)

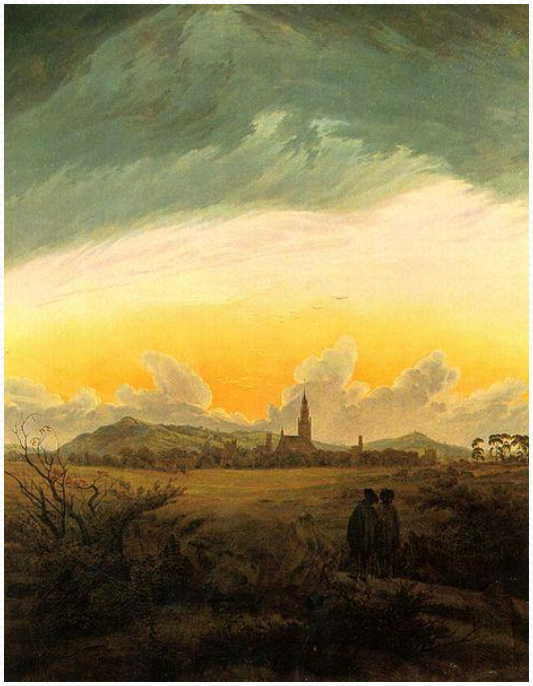
"The totality of hues symbolizes the cosmic significance of the epochal event" [Itten,1961]

Rogier Van der Weyden: Deposition (1436)
Primary triad - red, yellow, blue
[Koenig, 2010]

Cezanne: Apples and Oranges (1895-1900)
Double Complementary - red/orange and green/blue
[Itten,1961]

Examples - Cold-warm

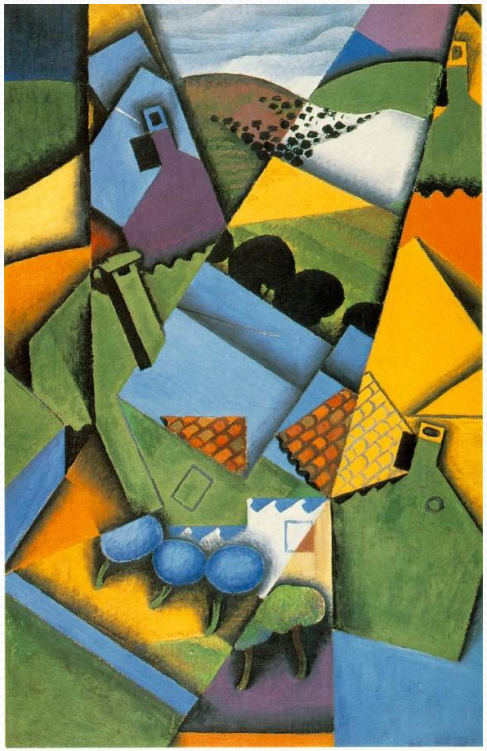
Friedrich:
Woman before the Setting Sun (1818)
Warm



Friedrich:
Neubrandenburg (1816)
Cold-*Warm*

Friedrich:
Monk by the Sea (1808)
Cold

Examples - Saturation



Gris:
Landscape with Houses at Ceret (1913)

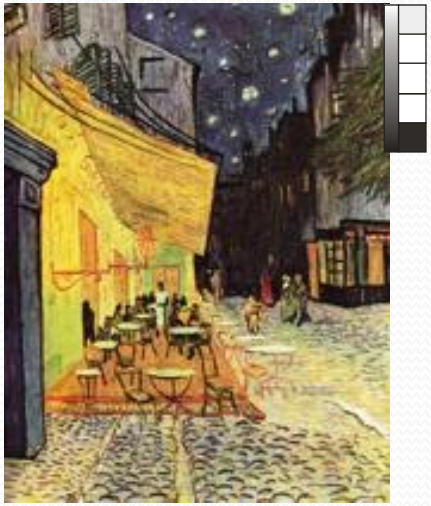
Braque:
Still Life with Mandola and Metronome (1909)

Examples - Light-Dark

Rembrandt: Portrait of Saskia (1633)
Light-Dark Contrast

Mucha: Flower Lily (1898)
Very Light

Monet: Water Lilies, 1908
Light-middle, smooth



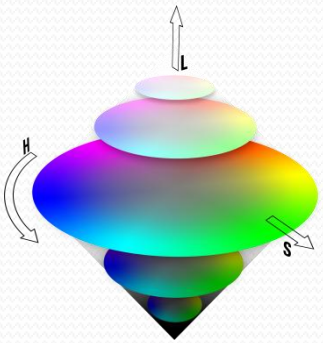
van Gogh: Cafe Terrace at Night (1888)
Light-Dark Contrast + Opposite hues Yellow/blue

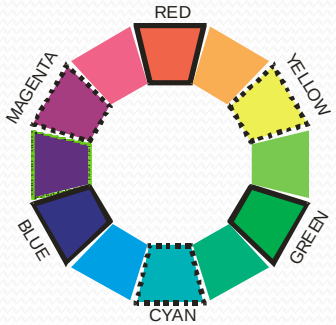
Monet: Water Lilies, 1915
Dark-middle, smooth

RGB, YCbCr, HSL

Colour models are intended to present the interconnections between colours.

- RGB - additive system used to describe colours in light sources.
- HSL - Hue, Saturation, Lightness





Hue: 0..360^0 and "-1" for achromatic;

Saturation: 0 (a shade of grey) to 1 (full sat.)

Lightness: 0 (black) to 1 (white)

Conversion from RGB to HSL:

R,G,B in [0,255]; max = max(R,G,B); min = min (R,G,B)

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

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

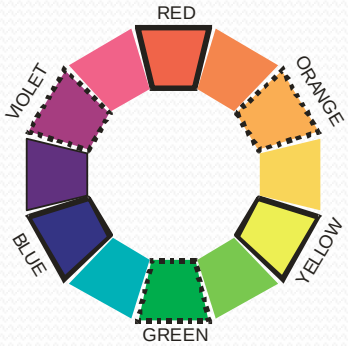
$$L = \frac{max+min}{2*255}$$

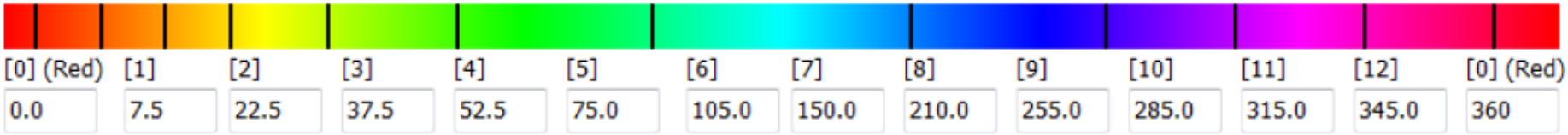
- YCbCr - the second primary colour model used in digital component video.

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

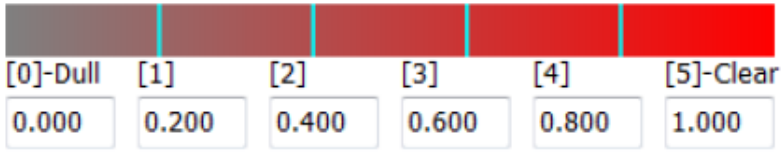
HSL-artists Colour Model

- Hue is based on the definition of Hue in the HSL colour model.
- But later, when we use quantization of the Hue, we take into account the misplacement of artists' colour wheel



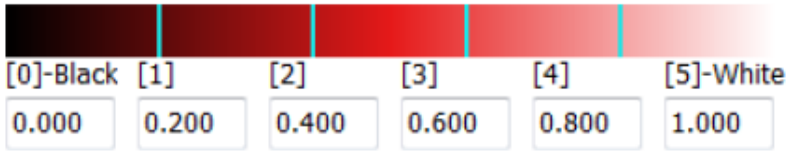


- Saturation - the same as in HSL



- Luma - given from YCbCr model
  (represents very accurately the brightness)

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



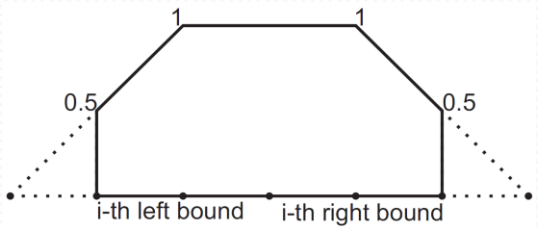
Low Level Colour Features

We use these three characteristics for two purposes:

- Analyzing the colour distribution in art images;
- Using them in the process of calculating higher-level colour harmonies and contrast features.

The quantization of Hue is made to NH=13 bins
("-1": achromatic; "0".."11": "red"..."magenta")
non-linear with respect to taking into account the misplacement of artists' colour wheel and Hue definition in HSL colour space

The Saturation and Lightness are linearly quantized into NS=5 and NL=5 bins



Fuzzy function for calculating quantization part of colour characteristic.

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

Hue Harmonies

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

Hue Order Vector - number of dominant hues nh , and positions of dominant hues, ordered in decreasing percentage.

- nh : 0 for achromatic paintings
- nh : the number of ordered hues, which sum of the percentages exceed some value x

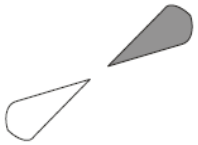
$(nh; p_1, p_2, \ldots, p_{nh})$, $nh \in \{0, \ldots, 5\}$, $p_i \in \{-1, \ldots, NH - 1\}$ and $h_{p_i} \geq h_{p_{i+1}}$, $i \in \{1, \ldots, nh - 1\}$

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

Hue Harmonies

Functions that reflect the mutual disposition of two colours.

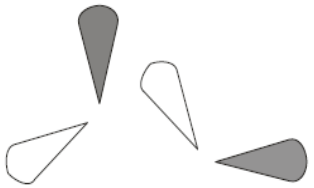
$$opposite(p) = \begin{cases} p + NH\ div\ 2 & if \quad p \le NH\ div\ 2 \\ p - NH\ div\ 2 & if \quad p \ge NH\ div\ 2 \end{cases}$$



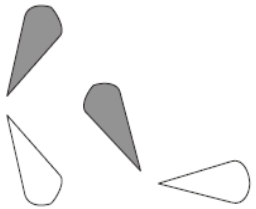
$$l\_neighbour(p) = \begin{cases} NH - 1 & if \quad p = 0 \\ p - 1 & if \quad p\ in\ \{1,\ldots,NH-1\} \end{cases}$$

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

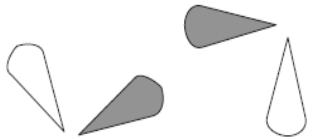
$$l\_triad(p) = (NH + p - NH\ div\ 3) \bmod NH$$



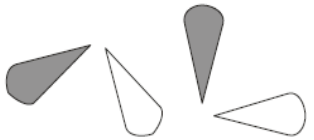
$$r\_triad(p) = (p + NH\ div\ 3) \bmod NH$$



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



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



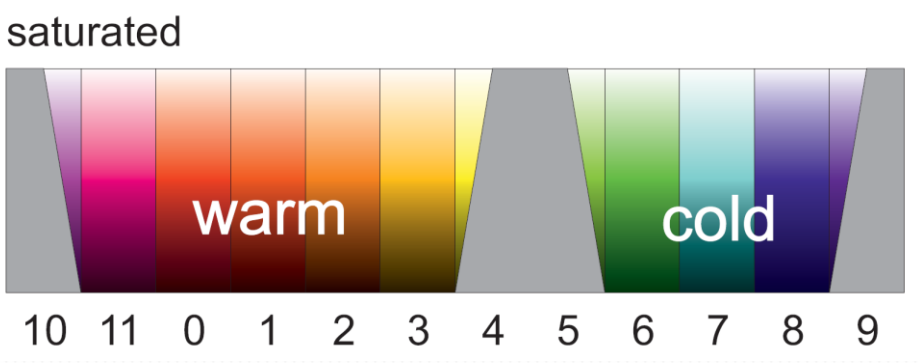
nh		Hue harmony/contrast
0		*Achromatic*: black, white and grey tones
1		*Monochromatic*: one hue predominates
2		*Analogous*: $p_2 = l\_neighbour(p_1)$ or $p_2 = r\_neighbour(p_1)$;
2		*Complementary:* $p_2 = opposite(p_1)$;
2		*Partial Triad:* $p_2 = l\_triad(p_1)$ or $p_2 = r\_triad(p_1)$;
3		*Analogous:* if for one of dominant hues $p_i,\ i \in \{1,...,nh\}$ the other two colours are $l\_neighbour(p_i)$ and $r\_neighbour(p_i)$ respectively
3		*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 $r\_neighbour(opposite(p_i))$
3		*Triad:* if for one of dominant hues $p_i,\ i \in \{1,...,nh\}$ the other two colours are $l\_triad(p_i)$ and $r\_triad(p_i)$
4		*Analogous:* if for one of dominant hue $p_i,\ i \in \{1,...,nh\}$ 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 $r\_neighbour(p_j)$
4		*Double Complementary:* if for one of dominant hue $p_i,\ i \in \{1,...,nh\}$ 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 $r\_neighbour(p_j)$
4		*Split Complementary:* if for one of dominant hue $p_i,\ i \in \{1,...,nh\}$ 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 $r\_neighbour(p_j)$
4		*Tetrad:* if for first hue p_1 the other hues are $l\_tetrad(p_1)$, $opposite(p_1)$, $r\_tetrad(p_1)$ respectively

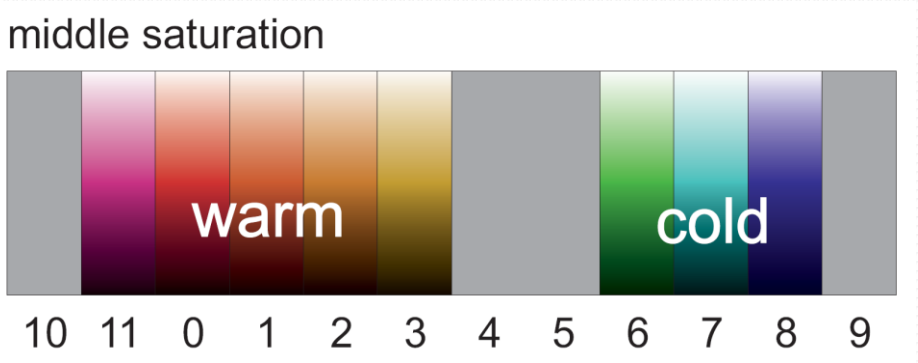
Cold-warm Contrast

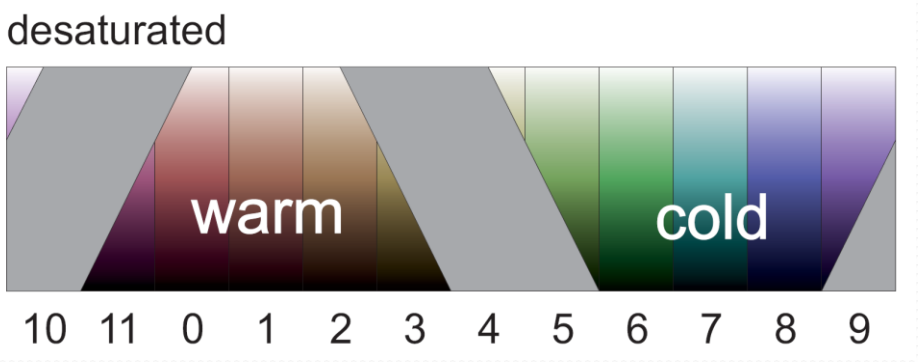
Families of colours:

p_{warm}, p_{cold}, $p_{neutral}$.

- *warm*
- *cold*
- *neutral*
- *warm-cold*
- *warm-neutral*
- *cold-neutral*

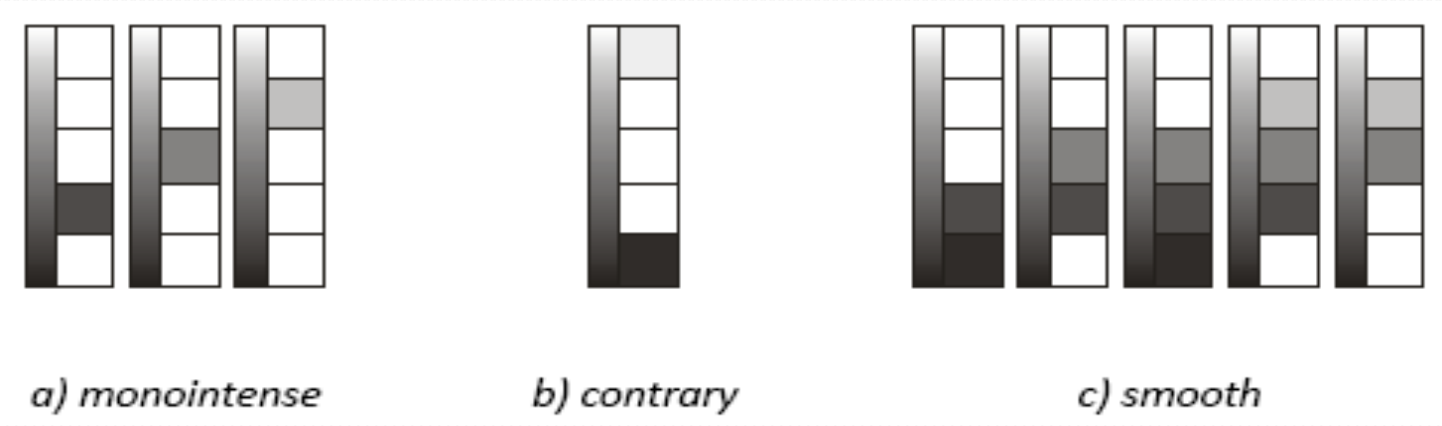






Saturation and Luminance

- Combinations



- Clear/Dull Contrast:
  - soft/sharp for light images,
  - ground/spectral for images with medium lightness,
  - dull/clear for dark images
- Light/dark contrast:
  - very dark, dark, middle, light, very light,
  - dark-light, light-dark, etc.

Local Features - VQ of MPEG-7 Descr. over Tiles

The next group of descriptors is based on vector quantization of MPEG-7 descriptors over the partitioned images.

They are used to analyze the possibilities of capturing more detailed information for semantic and abstraction content of art images based on the MPEG-7 descriptors:

- Scalable Color (SC);
- Color Layout (CL);
- Color Structure (CS);
- Dominant Color (DC);
- Edge Histogram (EH);
- Homogeneous Texture (HT)

Vector Quantization

- Splitting image into mxn non-overlapping tiles;
- For each MPEG-7 descriptor X∈{SC, CL, CS, DC, EH, HT}:
  - For all tiles of paintings feature vectors are calculated;
  - Clustering procedure for received vectors of the tiles from learning set is applied;
  - The naming of clusters is made (the number from clustering procedure);
  - Tiles from the learning set receives corresponded labels;
  - The centroids of clusters are calculated;
  - For the rest of the tiles, the membership of their centroids is calculated, and labeling of these tiles is made.

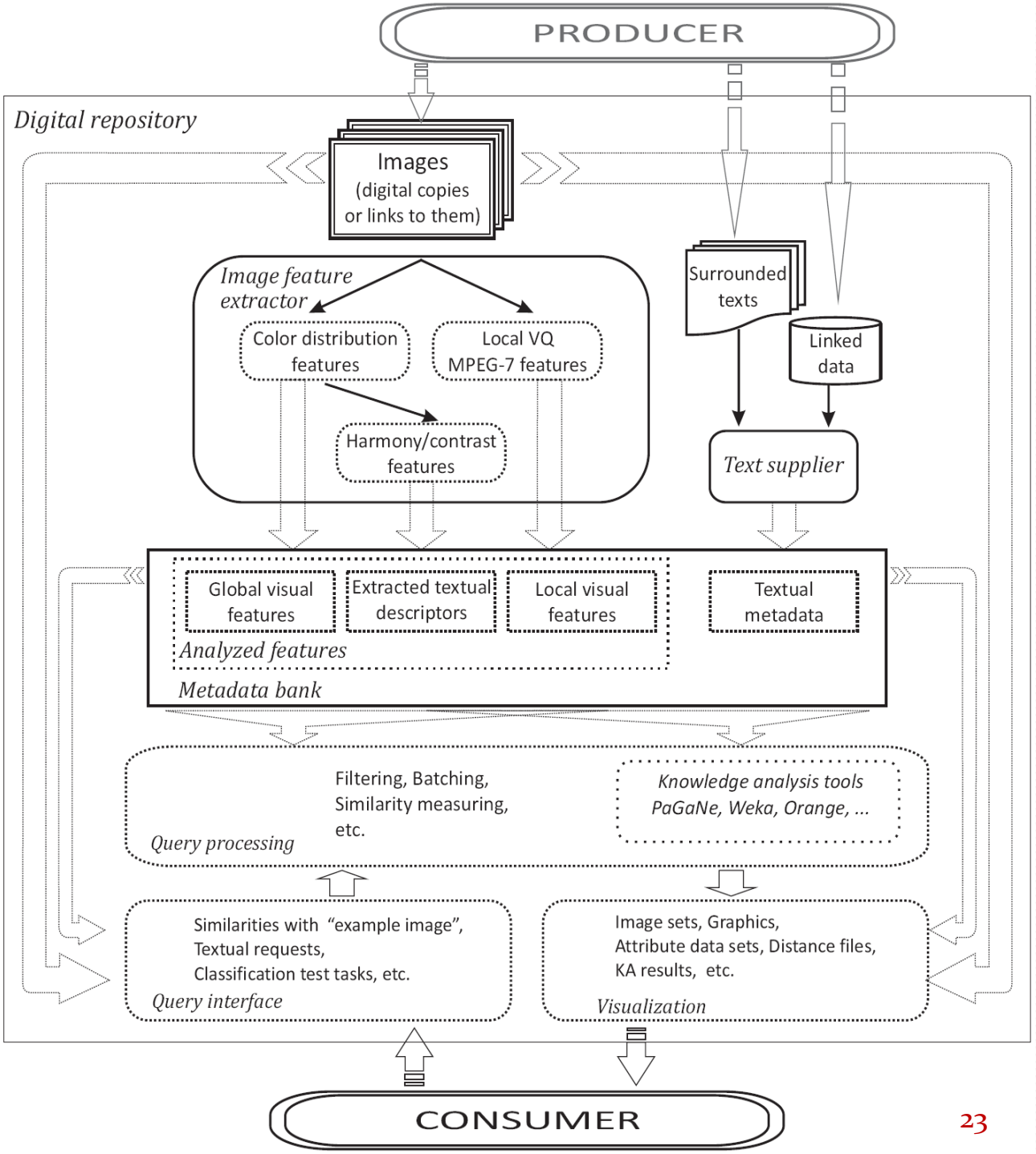
APICAS

Its main functions are:

data entry support:
- *choosing the collection;*
- *setting up parameters;*
- *selecting the LS samples;*
- *test textual metadata;*

visual characteristics extraction:
- *colour distribution;*
- *harm./contrasts' descriptors;*
- *local VQ-MPEG7 features;*

data delivery:
- *examining colour distribution;*
- *multidimensional scaling;*
- *knowledge analysis;*
- *visualizing;*
- *statistical and DM analysis.*



APICAS - Connections with other tools

- Multimedia Content Management System **MILOS**
  (*obtaining the MPEG-7 descriptors*)
- **CLUTO** open source software package
  (*clustering algorithm*)

- Open component-based DM and ML software suite **ORANGE**
  (*multidimensional scaling*)
- Waikato Environment for Knowledge Analysis **WEKA**
  (*classification algorithms*)
- DM environment **PaGaNe**
  (*class-association rule classifier PGN*)

Experiments - Data set

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

Classifiers Used for Predictive Analysis

Weka implementations:

- OneR - the simplest representative of decision rules [Holte, 1993]
- JRip - decision rule classifier RIPPER, which use a MDLP as stopping criterion for adding more conditions to a rule [Cohen, 1995]
- J48 - decision tree classifier C 4.5 [Quinlan, 1993]

PaGaNe implementation:

- **PGN** - class-association rule classifier, which strives for maximal accuracy of produced rules and uses a coverage measure in the classification stage [Mitov, 2011]

Descriptive Analysis Visual Features

Hue:

The predominate presence of colours in red-orange spectrum:

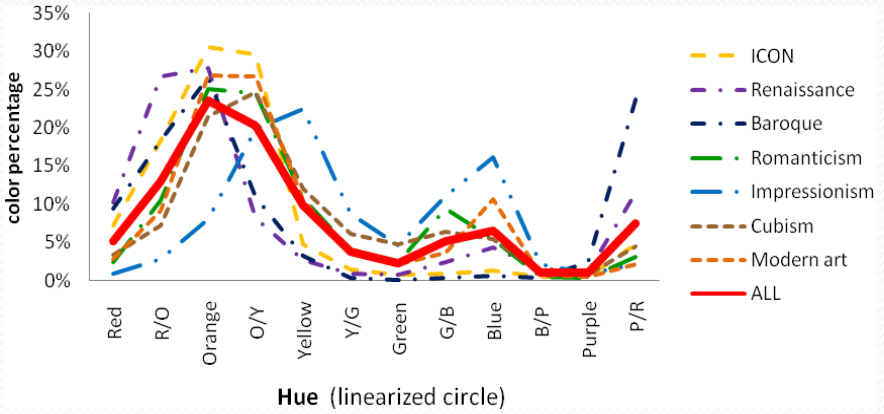
- colouring of faces and bodies
- using the materials and varnish, which acquired yellowish tinge.
- cold hues as blue and green are non-durable under the influence of light
- some technical artists' practices of some movements excluded the green colour – it was replaced by brown.

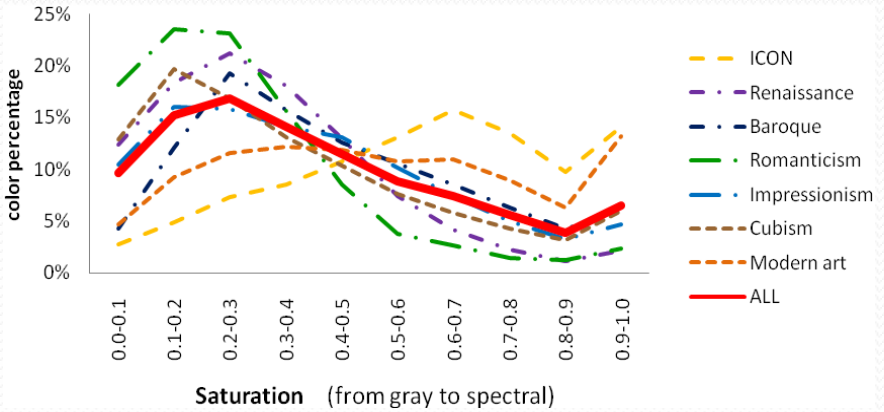
Saturation:

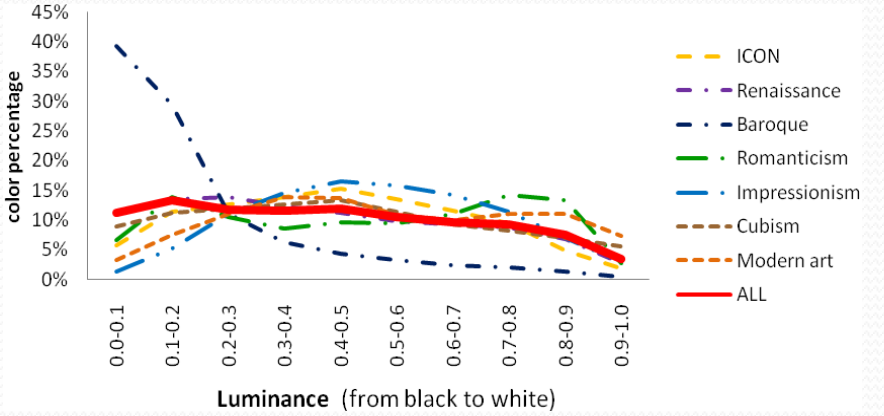
- the most distinctive is Icon style - usually Hue-contrast with pure colours is used.

Luminance:

- common trends for most of movements
- only Baroque is considerably different.



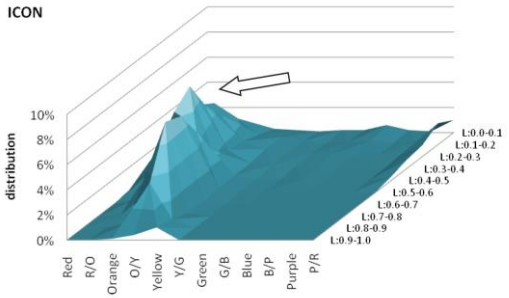


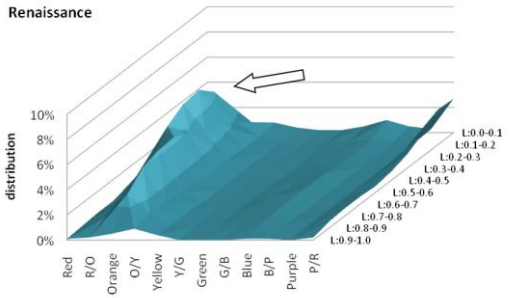


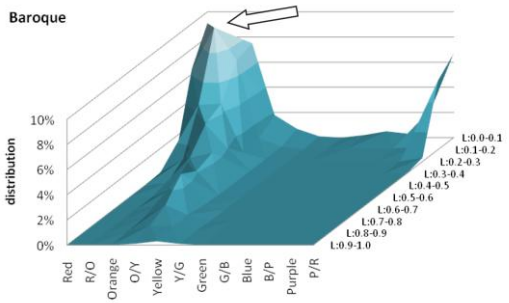
Descriptive Analysis Visual Features

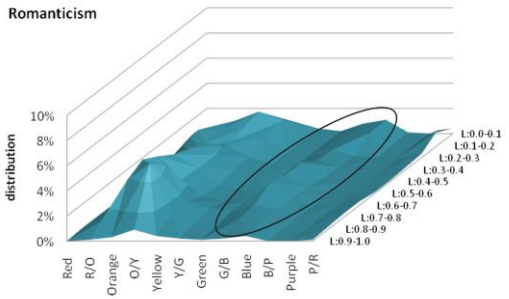
Colour distribution on two projections - hue and luminance:

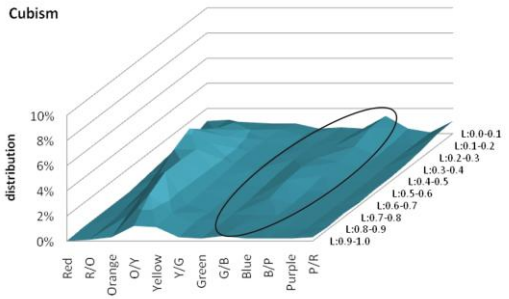
- predominance of dark orange colours in art paintings for Baroque
- predominance of warm colours, but in light tones in Icons
- In more contemporary movements blue tonality has stronger presence – lighter in Impressionism and darker in Modern art.

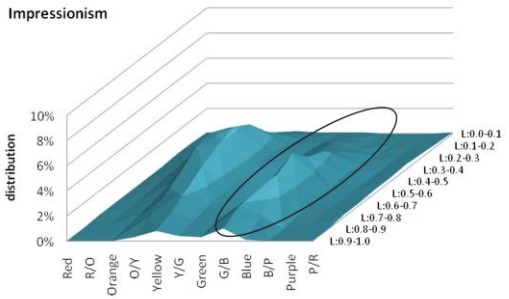


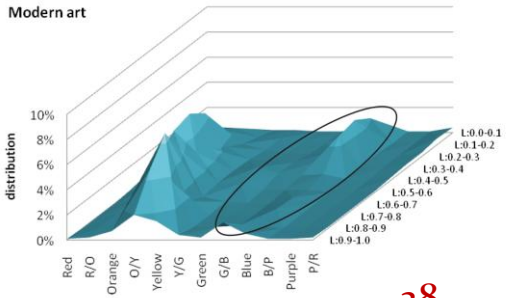






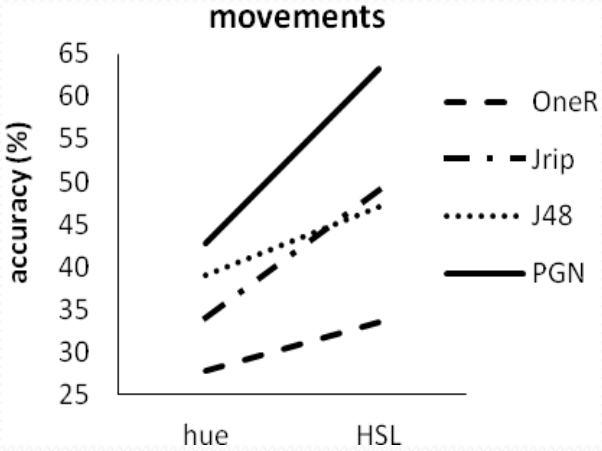


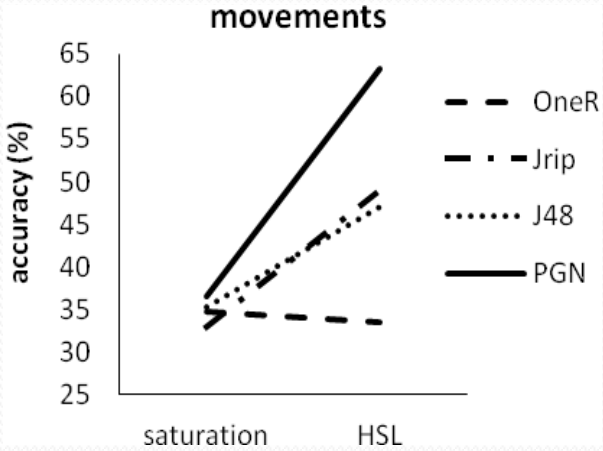


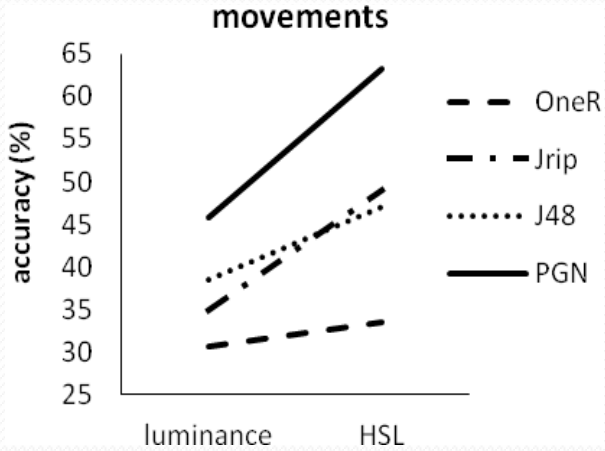


Predictive Analysis - Visual Features

- The accuracy of different classifiers by hue, saturation, luminance separately and all three together (three-fold CV)



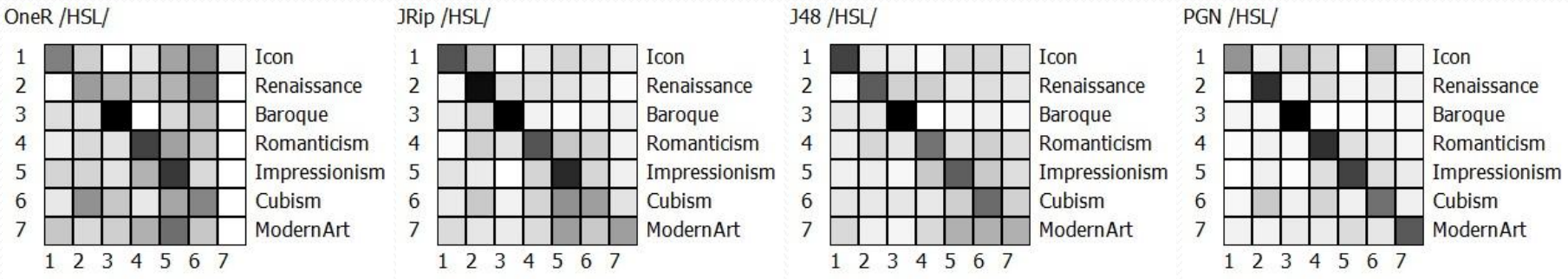




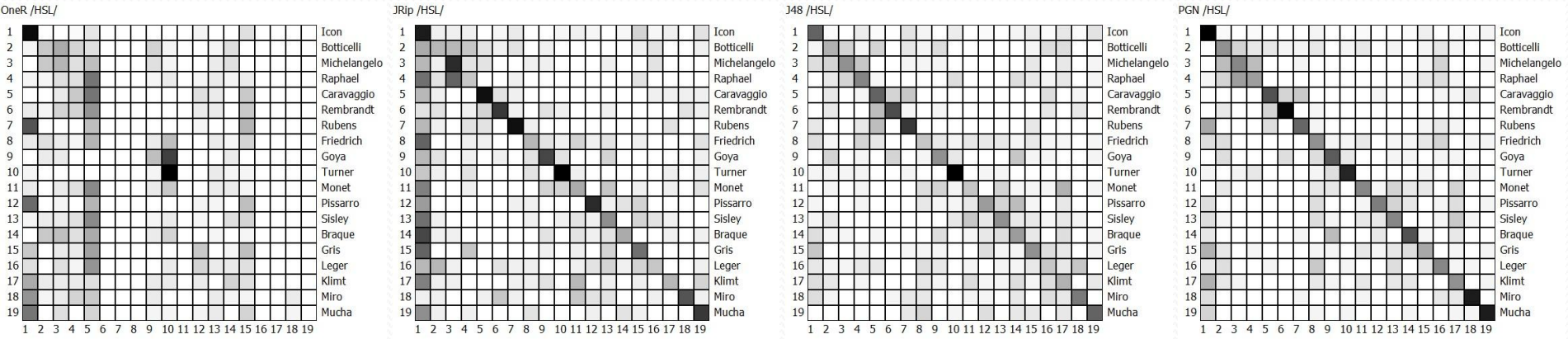
PGN shows the best accuracy from examined models for all datasets.

Additionally PGN shows the best possibilities to explore specific combinations of attribute values.

Confusion Matrices - Visual Features



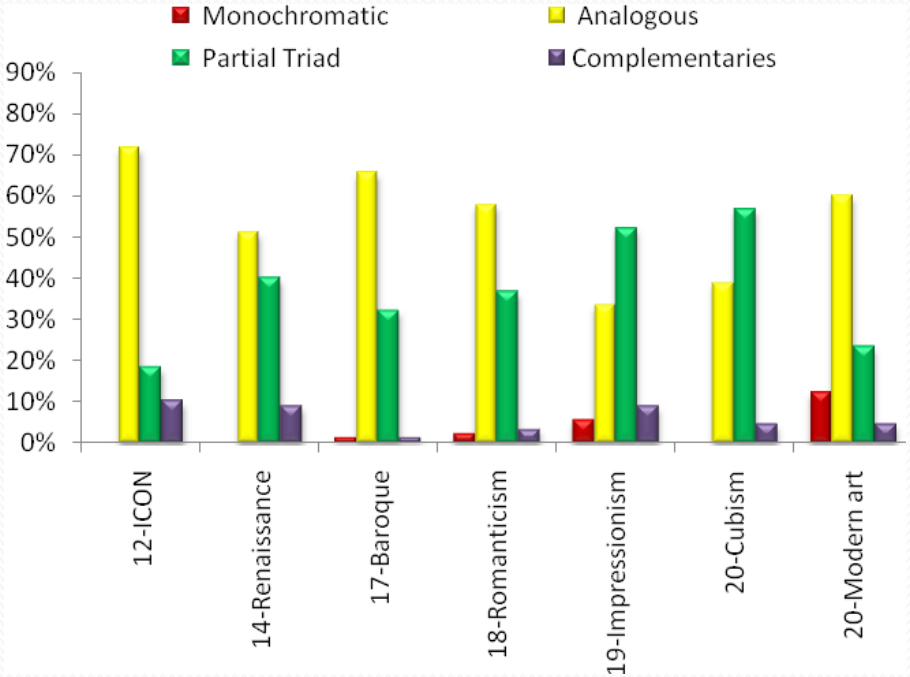
The Baroque movement is the easiest to predict; OneR fails to predict Modern Art;
PGN is the only classifier with a smooth consistent black/gray downwards diagonal.

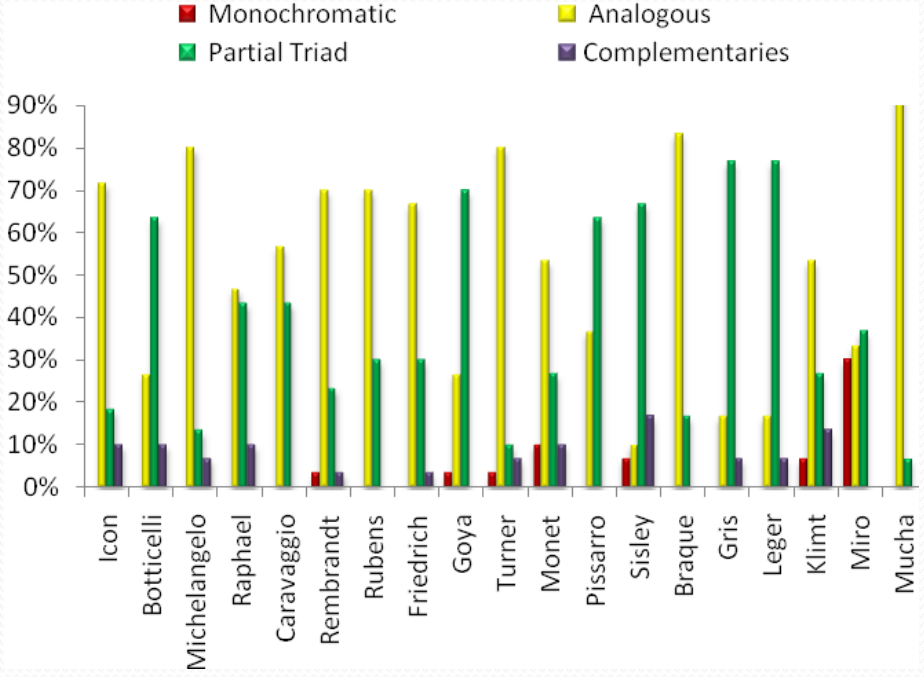


OneR is not able to classify the different artist paintings.
JRip predicts almost 25% of the paintings in artists case as Icons
(specific distribution of artists presentations – equal number, except Icons)

Descriptive Analysis - Harmonies/Contrasts

Percentage of different hue contrasts in the paintings

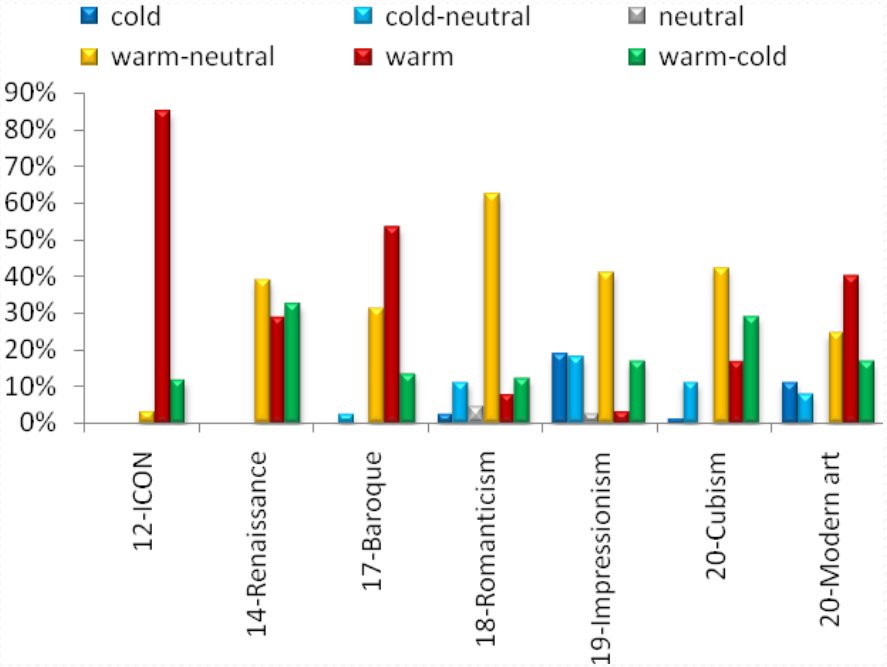




- Partial triads - natural paintings (Pissarro, Sisley).
- Instead of high abstractionism of Cubism Partial triads are used often (Gris, Leger)
- Triads: in paintings from authors, which techniques are based mainly on hue contrasts (Botticelli and Goya)
- Monochromaticity and analogous harmonies: where other key expressions are used (light-dark contrast in Baroque; gradient expressions in Cubism (especially Braque style))

Descriptive Analysis - Harmonies/Contrasts

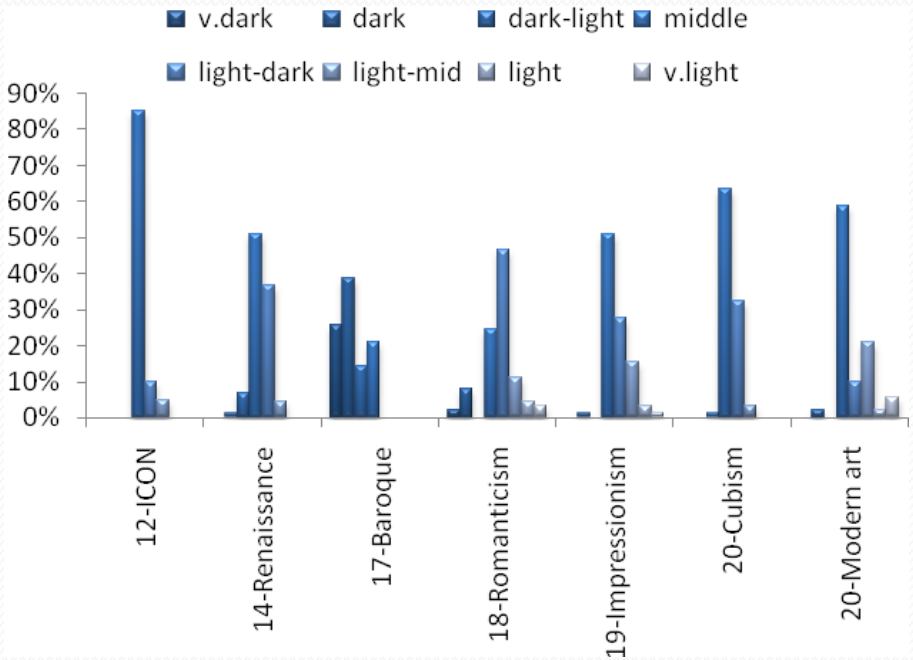
Distribution of paintings, based on cold/warm contrast



- warm in Icons: Orthodox tradition for using gold paints and red colour (symbol of sacrificing)
- dark warm colours: specific for the Baroque.
- cold tones: presenting the nature in paintings in Romanticism and Impressionism

Descriptive Analysis - Harmonies/Contrasts

Distribution of lightness in paintings from different movements

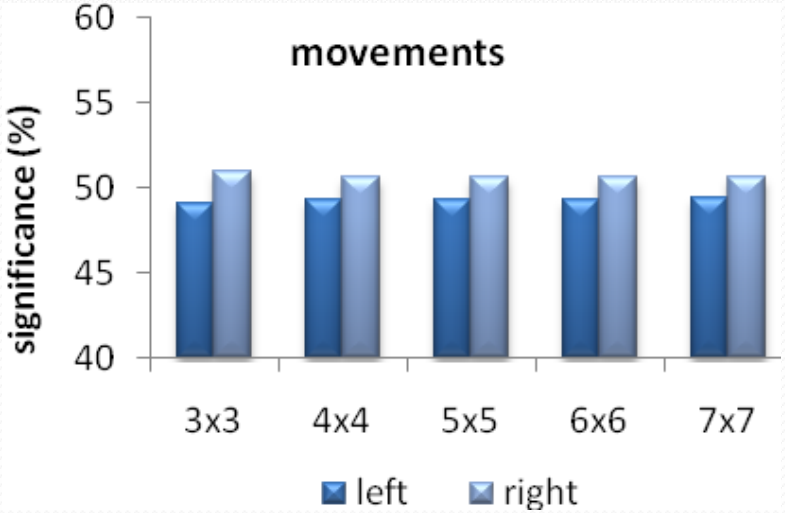


- Baroque: dark colours and dark-light contrast - using the techniques of oil-paints (from one side - search maximal expression; from the other - paint in the candle lights in studios)

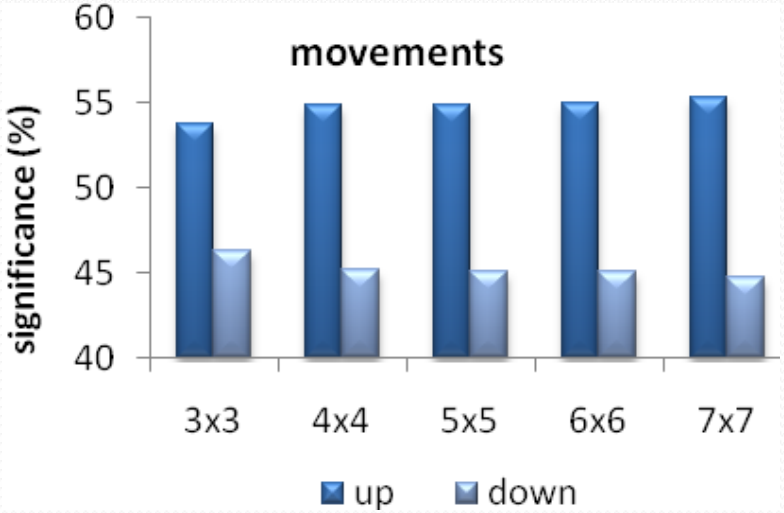
- Impressionism: special attention on the study of sunlight (the factory started producing paints in tubes that gave the possibility of the artists to go to paint outside)

Analysis of Local Features

Distribution of significance of **left side and right side** of the images with different tiling



Distribution of significance of **upper and lower zone** of the images with different tiling

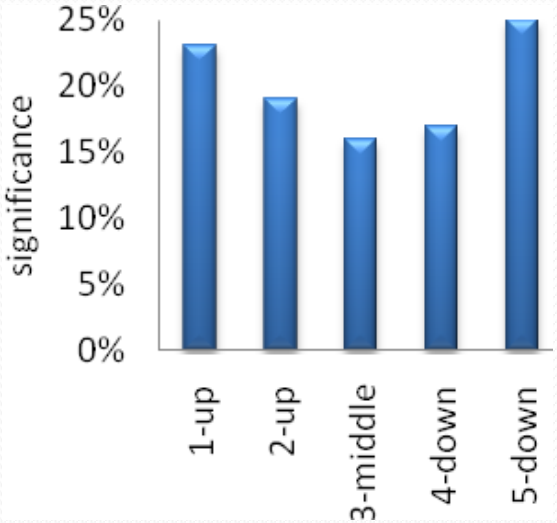


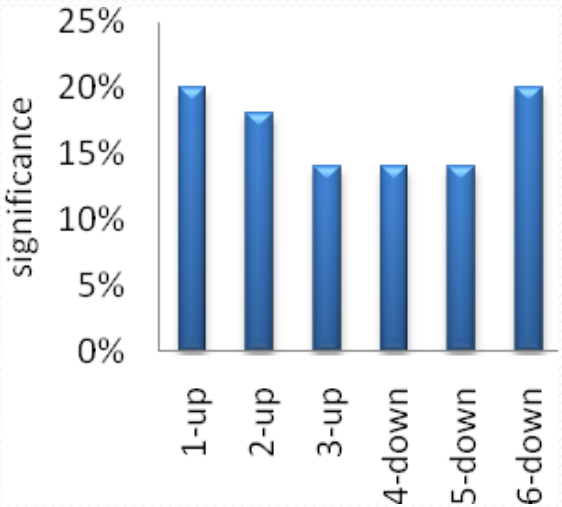
The construction of many classical paintings is based on central symmetry of concept disposition.

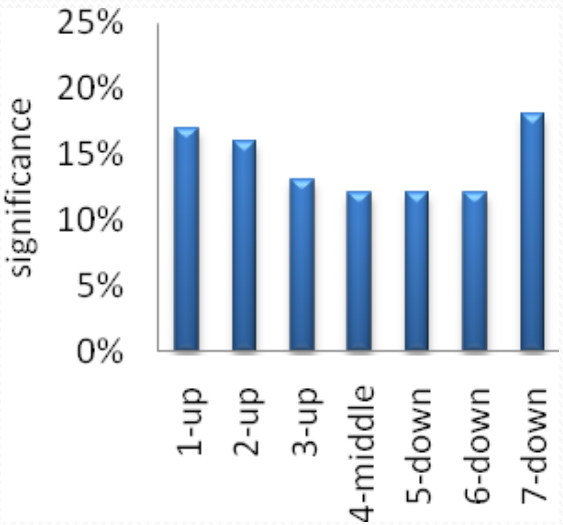
A little superiority of the right part of the image confirms the results from psychological theories for understanding human perception [Arnheim, 1974].

Analysis of Local Features

Distribution of significance of the tiles by **position of height** (1..n: up to down)

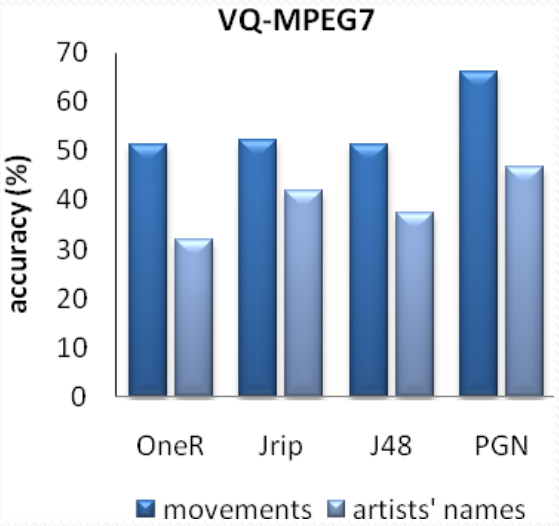


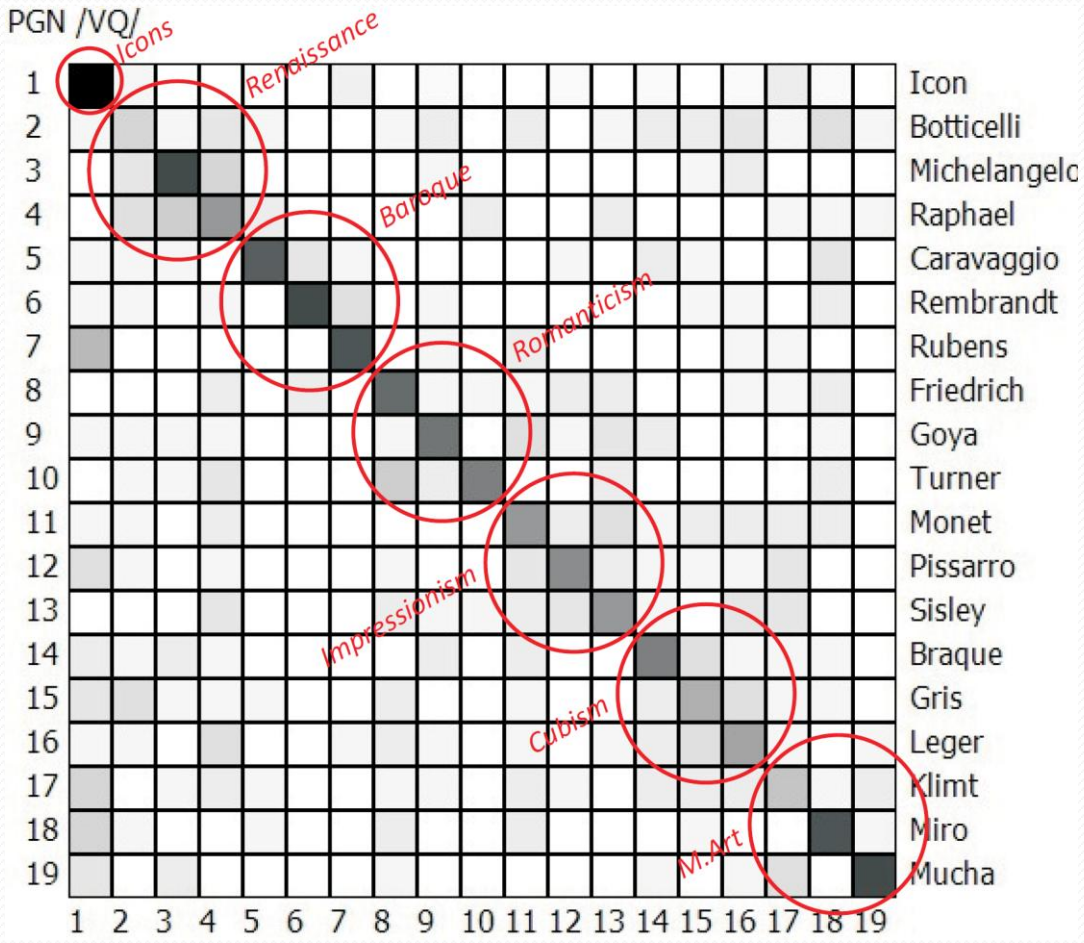




While the central part of the image brings objects or scene information, the borders are less burdened with this task.
In order to supply the focus of the image, there are not usually specific objects found here, but only the ground patterns, which are specific for the artists or the school.

Predictive Analysis of the VQ-MPEG Descr.





A local misclassification within the frame of movements -
mainly for Renaissance and in some degree for Impressionism and Cubism.

Conclusion …

- We propose a colour model appropriate for contrast characteristics extraction constructed as a combination of three other models. The model is easily comprehensible while also allows 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 propose an experimental CBIR system architecture as an environment for applying the suggested 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 selected image by one or more of the extracted features;
  - search of images that satisfied user queries featuring contrasts' characteristics;
  - investigation on the possibilities to integrate such characteristics within specialized resource discovery.

… and Future Plans

The plans for further research are focused on:

- Analyzing the possibilities of using SIFT-descriptors 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 new developed attributes and corresponding methods in the field of analysis Eastern Iconographical painting schools (especially Bulgarian tradition) and themes within the icons.

Thank you for your attention!

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