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# ANALYSIS OF THE DISTRIBUTIONS OF COLOR CHARACTERISTICS IN ART PAINTING IMAGES

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Abstract. In this paper we study some of the characteristics of the art painting image color semantics. We analyze the color features of different artists and art movements. The analysis includes exploration of hue, saturation and luminance. We also use quartile's analysis to obtain the distribution of the dispersion of defined groups of paintings and measure the degree of purity for these groups. A special software system "Art Painting Image Color Semantics" (APICSS) for image analysis and retrieval was created. The obtained result can be used for automatic classification of art paintings in image retrieval systems, where the indexing is based on color characteristics.

**1. Introduction.** If one says "red" and there are 50 people listening, it can be expected that there will be 50 reds in their minds. One can be sure all of these reds will be very different [1]. Color is an experience, an insubstantial attribute of other things [2]. Colors are neither good nor bad in themselves. They

*ACM Computing Classification System* (1998): H.5.1, H.3.1, H.3.3.
*Key words:* Classification, Color, Image, Information retrieval, Multimedia.

do have a positive or negative, conscious or unconscious psychological effect on the viewer.

**1.1. Color theories.** Many color theories have been invented. Some of the main steps were the following. The first was in ancient Greece, where the people thought that colors arose from the struggle between light and darkness.

Pythagoras (c. 580–500 B.C.) developed a mathematical theory of "harmony of the spheres" about the planets. He included colors correspondents to the musical scale.

Aristotle (c. 384–322 B.C.) suggested that all colors are derived from black and white.

In the late Middle Ages heraldry became a highly developed discipline. Tinctures are the colors used. The names used in English blazon for the metals come mainly from French, and include Or (gold), Argent (white), Azure (blue), Gules (red), Sable (black), Vert (green), and Purpure (purple). They have particular meanings.

Leonardo da Vinci (1452–1519) wrote about how mixing pigments affects the philosophical meanings of the colors.

Isaac Newton (1642–1727) split sunlight into its components. He established the fundamentals of color theory in his Optics [3] in 1704.

Johann von Wolfgang Goethe (1749–1832) in [4] (1791) studied the emotion and psychological influence of colors. His six-hue spectrum of colors remains the standard for artists even nowadays.

Albert Munsell (1858–1918) proposed a color system in [5] (1921). It is a numerical three-dimensional space, based on hue, value and saturation.

Otto Philip Runge (1770–1840) in 1810 established the basis of the theory of the complementary colors.

Johannes Itten (1888–1967) proposed a taxonomy of colors based on hue, luminance, and saturation that provided the basis for his color theory [6] (1963). It is particularly well-suited to describe the human experience of color (warm, cold, contrast, harmony) and therefore the theory provides a foundation for formalizing high-level semantic information about images. In this theory color aesthetics may be approached from impression (visually), expression (emotionally) and construction (symbolically). He developed a new kind of color wheel that changed the way color was seen, influencing artists and designers right up to the present moment. He stressed: "Color is life, for a world without color seems dead. As a flame produces light, light produces color. As intonation lends color to the spoken word, color lends spiritually realized sound to form".

Many artists and scientists gave important results in the color theory.

Some of them are: Jacques Christophe LeBlon (1667–1741), Moses Harris (1731–1785), Michael Eugene Chevreul (1786–1889), Wilhelm Ostwald (1853–1932), Wilhelm von Bezold (1837–1907), Ludwig Von Helmholz (1821–1894), Josef Albers (1888–1976) and more.

**1.2. Colors in the art painting images.** The most used color spaces from the artists are the ones, in whose ground lie the three basics attributes of the color: the name of the color (Hue), the purity (Saturation) and lightness (Value, Luminance).

The artist's spectrum (color wheel) is the circle which illustrates the visible hue in order: red, orange, yellow, green, blue, violet, and closes to the first color – red. Primary colors are red, yellow, blue and secondary colors – green, orange and violet. Between them are tertiary colors, receiving by mixing of two neighbor colors. Instead of chromatic colors, the artist used also achromatic colors, which are variation of black-white scale. Saturation shows purity or dullness of the color. Dulli colors are obtained by mixing pure chromatic colors with gray color. Value or Luminance shows the relative lightness or darkness.

The artists start with a sketch and then begin applying the first coat of paint. They first define the contrast of the composition by using only black, white and shades of gray. When the gray coat is complete they begin adding color. They choose colors that have the same lightness or darkness as the gray underneath. That way, they are sure to create a well defined composition with optimal contrast. The choice of colors together with the balance between the forms gives the atmosphere of the art. Some of the paint movements are based on colors such as impressionist works.

**1.3. Fine art computer systems.** Some art computer systems are analyzed below briefly. Their choice is made in order to illustrate the various features that they support.

***A lightweight image retrieval system for paintings*** [7]. The image indexing features are divided into the following three groups:

- Canvas features: max, min, mean, median, and standard deviation from each of the red, green, and blue color channels;
- Color features: intensity mean (measures the global brightness of a grayscale image), color frequency distribution (measures the degree of disorder found in the frequency distribution of colors in a painting);
- Edge characteristics: line count (uses the Sobel edge detector to identify lines in the image).

***Art historian system*** [8]. The system contains an automatic extraction of features of paintings' art movements. It is shown that the feature set enables one to highlight art movements efficiently. In the classifier design, statistical pattern recognition approach is exploited using Bayesian, k-NN and SVM classifiers. In this study, it has been shown that the art movements of paintings can be indexed by exploiting the following six measures:

- Percentage of dark colors;
- Gradient coefficient calculated from the gradient map of the painting image;
- Number of local and global maximums in the luminance histogram;
- Color range that the peak points of the luminance histogram corresponds;
- The deviation of average grey level acquired within each block from the average grey level acquired within an entire image;
- "Skew" – the deviation of grey level distribution from Gaussian distribution.

***The pictorial portrait database*** [9]. The system uses a hierarchical database indexing method based on Principal Component Analysis. The description incorporates the eyes, as the most salient region in the portraits. The algorithm has been tested on 600 portrait miniatures of the Austrian National Library.

***PICASSO system*** [10]. The system hurdle a multiple descriptions of each data set, each one covering a different level of precision. Images are analyzed at several levels of resolution in order to obtain a pyramidal segmentation of color patches. Each region at level $n$ is obtained by clustering adjacent regions at level $n$-1. Region energy measure is associated to each region. This energy is obtained as a weighted sum of three entries: the area, the color uniformity and the color contrast.

***Free hand drawings of Eugene Delacroix system*** [11]. S. Kröner and A. Lattner trained a naive Bayes classifier to distinguish from those of comparable artists with using only five measures: three of them measure the ratio of black and white pixels and two are measuring the stroke direction.

***Painting classification system.*** D. Keren [12] proposed a framework for classification of paintings based on local features derived from coefficients of a discrete cosine transform. After calculating the local features, each pixel is classified and the overall classification of the image is determined from a majority vote of the pixel values. The testing set comprises the works of Rembrandt, Van Gogh, Picasso, Magritte, and Dali.

Different tools are used to analyze the art images in order to enhance their search. Usually a set of ontologies, including the Art and Architecture Thesaurus [13], WordNet [14] and IconClass [15] are used. The knowledge is represented in Resource Description Framework Schema (RDFS), a W3C standard for semantic annotation. The ontologies are represented as a subclass hierarchy of RDFS classes [16].

**1.4. Art painting image color analysis.** The painting beauty comes from locking hues into coherent, harmonious relationship [17]. Colors influence each other, and are influenced by each other, in predictable way [2]. There are a lot of researchers working in this area. Some of the most interesting works are presented below. Using color and texture indexing to improve collaborative filtering of art paintings is presented in [18]. The color characteristics in search engine are classified in [19] and [20]. Art movement classification on the base of colors is shown in [21]. Image retrieval by color semantics we found in [22]. In [23] image retrieval is based on high level color properties. Six specific types of contrasts are identified: Contrast of hue, Light-dark contrast, Warm-cold contrast, Complementary contrast, Simultaneous contrast, and Contrast of saturation. Some semantic issues in art painting image are discussed in [24].

**1.5. Paper goal and organization.** In this paper, we study some characteristics of the art painting image color semantics. We analyze the color features of different artists and art movements for classification purposes. The analysis includes exploration of hue, saturation and luminance. We also use quartile analysis to obtain distribution of dispersion of certain groups of paintings, and how to measure the degree of purity of these groups. A special software system “Art Painting Image Color Semantics” (APICSS) for image analysis and retrieval was created. The obtained here results can be used for automatic classification of art paintings in image retrieval systems, where the indexing is based on color characteristics.

The rest of the paper is organized in the following way. Section 2 presents the tools developed for art paintings color semantic’ analysis. Section 3 describes some results obtained from such analysis. In Section 4 some conclusions and future work directions are highlighted. Some of the results are given in the Appendix.

## 2. Art Painting Image Color Semantics Analyzing Tools.

**2.1. Formal description of the proposed method.** Let us have an image database with $N$ images. Let $S = \{p_k | k = 1, 2, \dots, N\}$ be the set of $N$ vectors representing the characteristics of these $N$ images.

The vectors of the set $S$ can be divided into several, say $g$, subsets (groups), which contain paintings from one artist, from the same movement, from the same century or another distinguishing feature. Let $P_j = \{p_i | i = 1, 2, \ldots, n_j\}$ denote the set of vectors, representing the group $j$, where $n_j$ is the number of the vectors in $j^{\text{th}}$ subset $(j = 1, 2, \ldots, g)$.

The paintings, which belong to group$j$, corresponding to the vectors of the set $P_j$, we call "***own***" paintings. The paintings, corresponding to the vectors from the set $S \backslash P_j$ (i.e. which do not belong to the set $P_j$) we call "***foreign***" paintings. For every group $j$ $(j = 1, 2, \ldots, g)$ we calculate the mean vector $\mu_j = \dfrac{\sum_{i=1}^{n_j} p_i}{n_j}$. For every vector $p_k \in S$, $k = 1, 2, \ldots, N$, representing a painting in our image database, we calculate the distance $d_{jk} = d(\mu_j, p_k)$ between the mean vector $\mu_j$ and vector $p_k$. Here we mean the Euclidian distance. However, any other distance between vectors could be used. Possibly, the Mahalanobis distance is more appropriate for the classification purposes since it takes into account the correlation structure within the vector components. The distances $d_{jk}$ for the "***own***" paintings $p_k \in P_j$ we arrange in ascending order. We also calculate the vector-quartiles of this set $Q_j^1$, $Q_j^2$, $Q_j^3$. The quartiles are values of the boundaries, which divide the ordered data set in each marginal measure, into four parts (sub intervals), so that each part contains equally $1/4$-th of all the values of this measure (i.e. $1/4$ of all elements from the entire set belong to each of the 4 groups) [25]. Other interesting value is the highest distance $d_j^{\max} = \max(d_{jk} | p_k \in P_j)$ between the mean vector $\mu_j$ and the vectors from the set $P_j$ of considered group $j$. Let us consider the set of distances between mean vector $\mu_j$ and "***foreign***" paintings for the observed group $\overline{D}_j = \{d_{ji} | p_i \in S \backslash P_j\}$. For this set we calculate the percentages of the distances that are smaller than $Q_j^1$, $Q_j^2$, $Q_j^3$ and $d_j^{\max}$ respectively. These percentages show the degrees of intervention of "***foreign***" paintings in the zones around the mean vector, bounded by considered values $Q_j^1$, $Q_j^2$, $Q_j^3$ and $d_j^{\max}$.

**2.2. The APICSS system.** Special software system "Art Painting Image Color Semantics" (APICSS) was developed. The system works with JPEG files. The names of the files begin with the family of the artist, separated from the rest of the name with dash. The user can choose the directory for analyzing and characterizing some picture, which can be compared with others. The images are converted as HSL (Hue, Saturation, and Luminance) images. The advantage of an HSL image is that it is symmetrical to lightness and darkness, which is not the case with the HSV (Hue, Saturation, and Value) color space for example. Hue is represented as an angle on the color circle (i.e. the rainbow represented in a circle). This angle is measured in degrees. By definition red is 0 ° or 360 °. The other colors are spread around the circle. For instance: green is located at 120°, blue at 240°, etc. Achromatic colors are coded by "-1". The saturation and lightness are represented as percentages: 100% means full saturation, 0% is a shade of grey. Luminance also is expressed in percentages: 0% lightness is black, 100% lightness is white, and 50% lightness is "normal" according to [26].

For the purposes of the system we convert real values of measured characteristics into values from three-dimensional feature space: twelve hues are used for fundamental colors [6], plus one value for achromatic color; ten levels of saturation and ten levels of luminance are identified. As a result, every picture is represented with an array, containing coefficients of participation of colors with correspondingly measured characteristics of the picture. The system has possibilities to be reconfigured to use HSV color space. Another possibility is to choose what will be analyzed: the whole array, a simple projection of selected characteristics (an area from the picture), or projection of two characteristics (for instance, Hue and Luminance). One of the functions is to see pictures from a current directory most similar to the selected picture, using Euclidean distance between these representations (Figure 1).

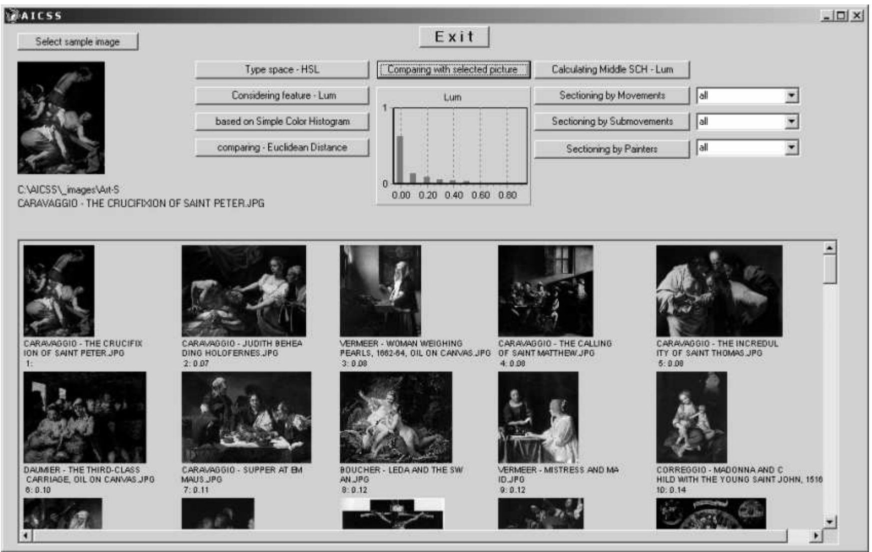



Fig. 1. Similarity search based on Euclidean distance by Luminance for "The Crucifixion of Saint Peter" of Caravaggio

The second class of functions is directed to carry out the analysis of selected characteristic, or of the whole space, as described in 2.1:

- For all pictures in current directory;
- For chosen movement or for all movements, available in the directory;
- For chosen sub-movement or for all sub-movements, available in the directory;
- For chosen artist or for all artists in the directory.

The names of the movements and sub-movements are described in a supporting file in the program directory. Also, it is described which artist belongs in which movement and sub-movement. A list of desired names of the artists is produced from the program during the execution on the base of the filenames. The result is displayed on the screen and in the same time is recorded as a text file in the program directory. Stored files can be used later for another analysis.

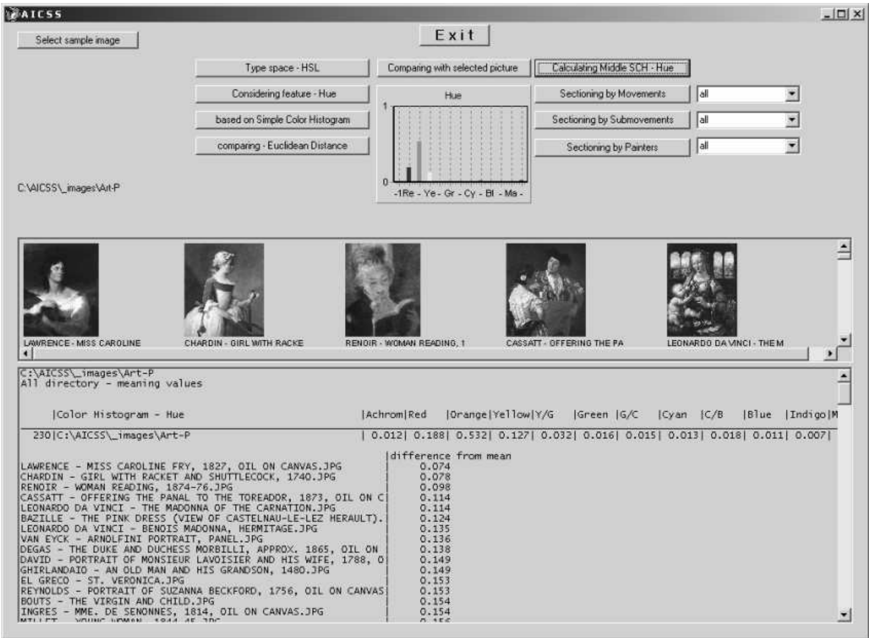



Fig. 2. The result of calculating the mean vector of Hue for sub-set “Portraits”

Figure 2 shows the result of calculating the mean vector for Hue for the sub-set “Portraits”. Beside the values of this vector, the system shows graphically resulting histogram for the Hue data set, and the pictures that are closely located to this mean vector in the group of “Portraits”.

**3. An Experimental Study.** We used about 900 art paintings from over than 100 artists, from different countries, representatives from the main museums of the main art movements in West-European fine arts, from Renaissance to Impressionism. Many interesting results were obtained. Some of them are briefly discussed below.

**3.1. Analysis of the color characteristics for different movements.** The APICSS was used for analyzing paintings from different periods. Table 1 shows in numbers and description what type of paintings are included in our experimental study. The paintings were separated in three basic groups: landscapes, portraits and subjects. The analysis is done over the whole image set and different subsets. The following movements (or groups) are included in our experimental study:

1. The **Renaissance.** This is a cultural movement from 14$^{\text{th}}$ through the 17$^{\text{th}}$ century. It is characterized with the revival of the values and artistic styles of classical antiquity and the development of perspective in painting [27].
2. **Baroque.** This period marks an era in the history of the Western arts roughly coinciding with the 17$^{\text{th}}$ century. The work that distinguishes the Baroque period is stylistically complex, even contradictory. Its salient characteristics (overt rhetoric and dynamic movement) are well suited to expressing the self-confidence and proselytizing spirit of the reinvigorated Catholic Church [28].
3. **18$^{\text{th}}$ century** includes several movements: **Romanticism, Rococo, Naturalism**, and **Realism**. In preliminary experiments these movements were considered separately, but now they are presented in common, since they use common techniques, but differ in thematic. Realism and Naturalism reply to political and social stirring of society, and the paintings from these movements get into category "Subjects". Rococo is another movement from this period. These artists used delicate colors and curving forms, decorating their canvases with cherubs and myths of love. Portraiture was also popular among Rococo artists. Landscapes were pastoral and often depicted the leisurely outings of aristocratic couples. Romanticism is oriented to viewing the new cult in the human perceptions, fusing with nature. Almost all of its paintings are in the category "Landscapes". The Romanticism is the movement when for the first time in the focus of painting became the painting of nature [**?**, chapter 11].
4. **Neoclassicism.** This is another movement from 18$^{\text{th}}$ century. Here it is represented separately, because it has a good number of samples in all three categories.

5. **The Symbolism.** It differs from the other movements, at first sight more philosophically, than technically. It was a continuation of some mystical tendencies in the Romantic tradition and it was even more closely aligned with the self-consciously dark and private Decadent Movement.
6. **The Impressionism.** This is a style of painting characterized chiefly by concentration on the general impression, produced by a scene or object, and the use of unmixed primary colors and small strokes, to simulate actual reflected light [29].

Table 1. Analyzed art painting images

| | **Landscapes** | **Portraits** | **Subjects** | **All paintings** |
|---|---|---|---|---|
| Renaissance | 8 | 66 | 167 | ***241*** |
| Baroque | 20 | 38 | 129 | ***187*** |
| Neoclassicism | 10 | 17 | 27 | ***54*** |
| 18th century | 33 | 46 | 95 | ***174*** |
| Symbolism | 5 | 12 | 40 | ***57*** |
| Impressionism | 81 | 46 | 96 | ***223*** |
| All paintings | ***157*** | ***225*** | ***554*** | ***936*** |

Some main findings are followed. For different groups the mean vectors have been calculated, along the histograms of the distribution of the respective characteristic within each group.

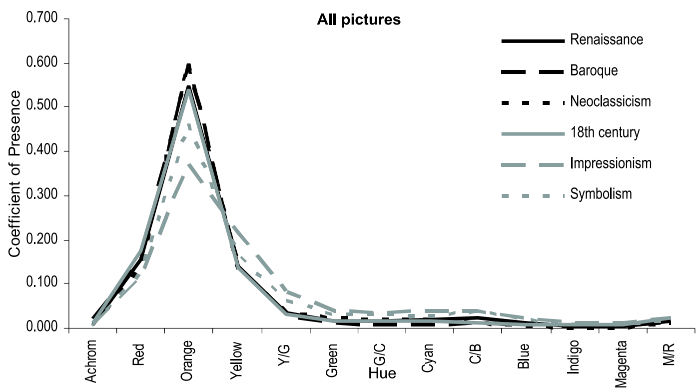



Fig. 3. The Hue distribution of all pictures, grouped by movements

Figure 3 shows the individual distributions of warm hues in the art painting images for selected movements. In spite of the intuitive expectations, the presence of cold hues in the groups of pictures, separated as landscapes (Figure 4), seems not so significant. Only the Impressionism shows a trend in its distribution towards this direction.

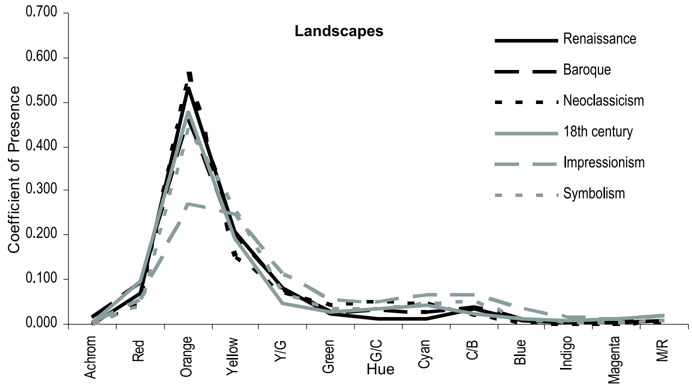



Fig. 4. The Hue distribution of landscapes, divided by movements

In paintings the predominate presence of warm colors are due to painting 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 (it can be noticed by the second pick on the right in each graph).

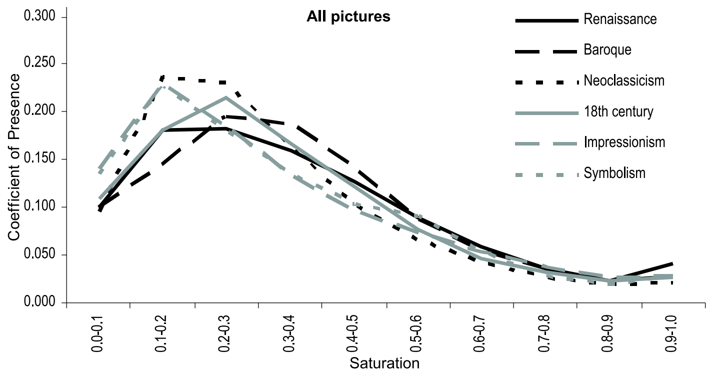



Fig. 5. The Saturation distribution of all pictures, grouped by movements

Figure 5 shows the distributions of saturation, for each of the six movements. The differences among these movements are obvious. The curves on the figure show the global trends of saturation distributions in examined database. Unfortunately, we do not have quantitative evidence for the significance in these differences.

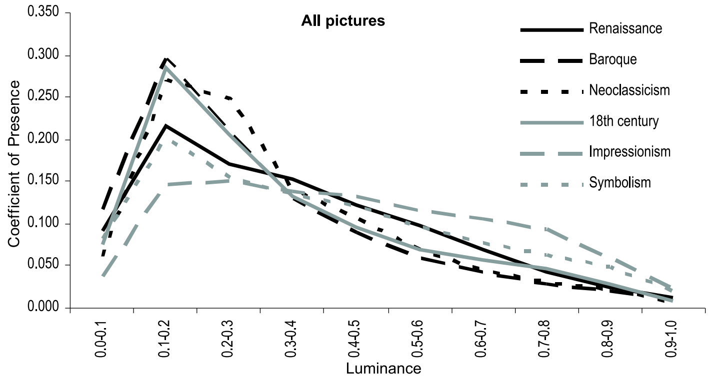



Fig. 6. The Luminance distribution of all pictures, grouped by movements

Figure 6 shows the distributions of the luminance within groups determined by movements. In the Baroque, Neoclassicism and $18^{\text{th}}$ Century many paintings are dark. It can be seen by the highest picks in the area of low values of the Luminance. Obviously, Impressionism and Symbolism exhibit trends towards lights.

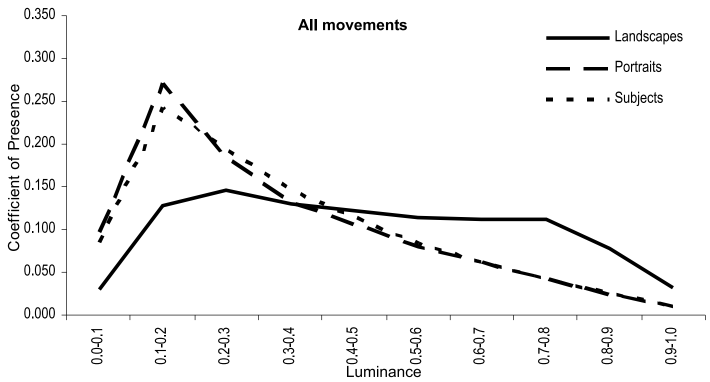



Fig. 7. The Luminance distribution of all pictures, grouped by types as landscapes, portraits and subjects

Figure 7 shows the distributions of Luminance for landscapes, portraits and subjects. The distributions of Luminance for portraits and subjects almost coincide. There is significant difference between distributions of Luminance for these two groups and landscapes. Landscapes exhibit a trend in direction of higher presence of light colors.

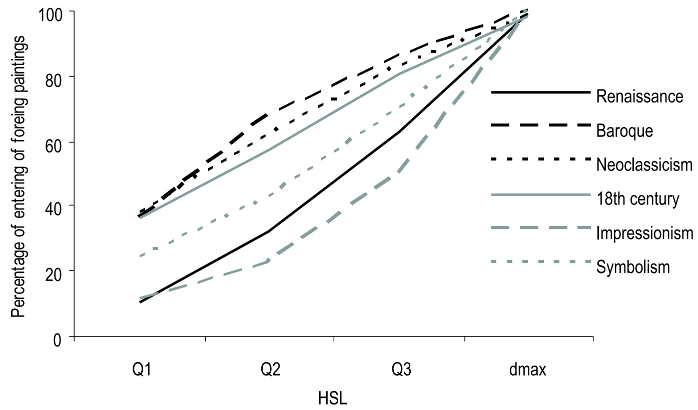



Fig. 8. Degrees of intervention of "foreign" paintings (groups = movements; feature = HSL)

The APICSS allows making more complex analysis on combination of projections of the color space. For instance, analysis of the color distribution on two projections – hue and luminance, has shown a predominance of dark red colors in art paintings. We are sure that by making groups when choosing other identity factors one may get other interesting distinctive distributions in regard of these groups.

We have implemented the analysis discussed in 2.1 on the values from the whole space HSL, based on groups of movements, described in Table 1.

The number of pictures, included in each group is shown on the last column of Table 1. The results are shown in Figure 8.

The analysis shows that at groups by movements, the displacement is relatively large from one group to another. It is based on different artists within the same group and different techniques that they used.

We notice the highest magnitude in the influence of the Impressionism and 18$^{\text{th}}$ Century painting, a bit less in the Neoclassicism, and lowest among the other movements.

In this respect, the Renaissance and Impressionism are less mixed than other movements. One reason is that in Renaissance there are used many frescos.

In the Impressionism we have different techniques, specially based on colors. The curves of Baroque, Neoclassicism and 18$^{th}$ Century show that they are more mixed with other color movements. Many of the pictures are painted with oils, which lend specific color distribution of the paintings.

**3.2. Analysis of the color characteristics for a particular artist.** Special analysis has been made about artists, from which there were more than 10 paintings in the observed set. These artists were: Blake (10), Bosch (10), Botticelli (13), Boucher (12), Cassatt (14), Cezanne (14), Constable (15), Corot (15), Correggio (10), Courbet (13), David (16), Degas (16), El Greco (16), Filippino Lippi (10), Fragonard (12), Friedrich (11), Gauguin (16), Ghirlandaio (12), Giotto (16), Goya (13), Hals (13), Hogarth (11), Ingres (11), Jordaens (12), Klimt (11), Lorrain (14), Manet (17), Mantegna (10), Monet (17), Morisot (15), Munch (14), Murillo (12), Piero della Francesca (11), Pissarro (19), Poussin (15), Raphael (10), Rembrandt (15), Renoir (17), Rubens (17), Seurat (14), Sisley (17), Steen (17), Titian (15), Van Dyck (12), Van Eyck (10), Van Gogh (15), Velazques (15), Vermeer (16). In the parenthesis the numbers of paintings in our image database are shown. For these artists several analyses were conducted.

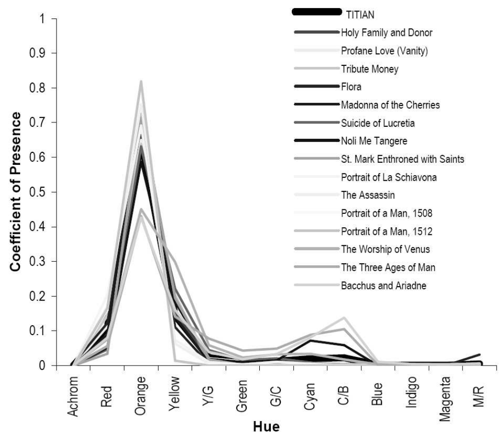



Fig. 9. The Hue Distributions of paintings of ***Titian*** (minimal standard deviation=0.1654)

We present two histograms for the Hue distribution of the paintings of Titian (Figure 9) and Morisot (Figure 10), which are the artists with minimum and maximum standard deviation for the vectors based on the Hue characteristic. The idea is to verify the common belief that if some characteristic is relatively

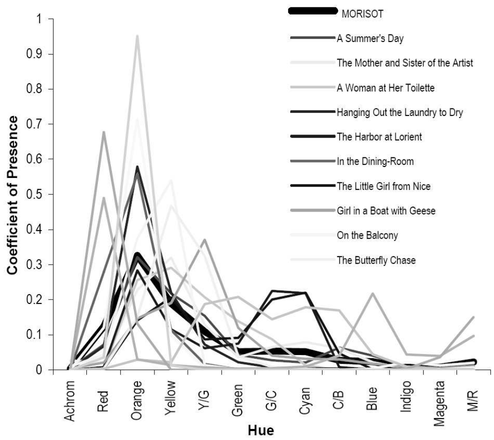



Fig. 10. The Hue Distributions of paintings of ***Morisot*** (maximal standard deviation=0.4061)

stable (measure of stability is reciprocal to the numeric value of the standard deviation) for some authors, for others it completely does not matter. In the case, Titian uses almost the same color relationships in his paintings (except for the two pictures "Bacchus and Ariadne" and "The Worship of Venus"). For the pictures of Morisot it is known that he uses significantly different relationships between the colors. The histograms in Figure 9 and 10 show exactly these features of the two artists.

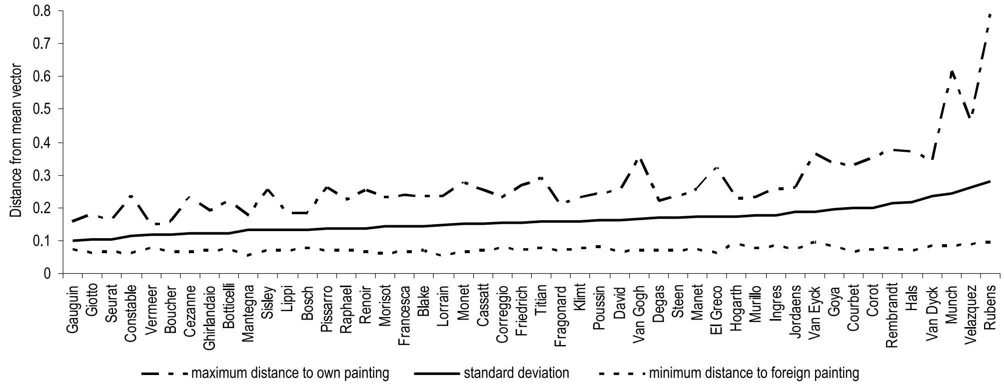


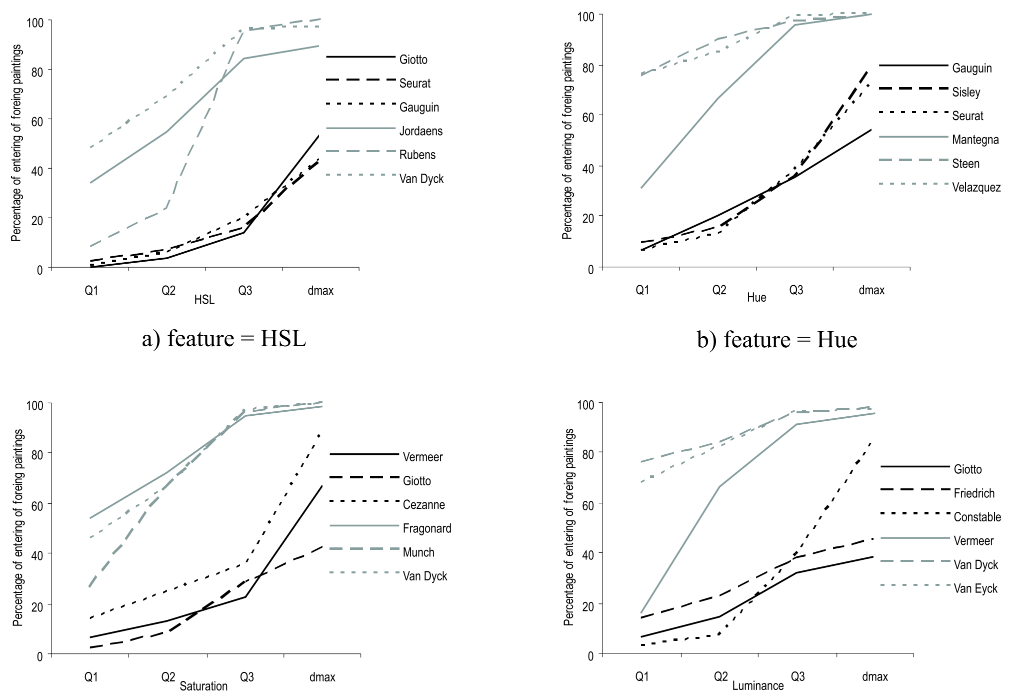

Fig. 11. The maximum distance of "own" paintings, standard deviation and the minimum distance of "foreign" paintings to the mean vector for all three characteristics for the groups, based on artists

The graphics in Figure 11 show the maximum distance between mean vector for HSL (all three characteristics) of the considering artists and “own” paintings – upper line, the standard deviation of the group – middle line, and the minimum distances between mean vectors and “foreign” paintings – lower line. The artists are sorted in order of increasing the standard deviation.

The graphics show which artist uses about the same style in all his pictures. For instance, for Gauguin maximum distance from mean vector to own paintings is 0.16 and the standard deviation from the mean vector is 0.09. It also shows which artist has used quite different styles in his pictures. For instance, for Rubens maximum distance from mean vector to own paintings is 0.79 and the standard deviation from the mean vector is 0.28.

The graph shows the penetration to the paintings of the foreign artists close to the middle-level vectors on every one from the artists. The next graphs show how unique is the vector for one artist.

Figure 12 shows first three and last tree rows of each table 2–5.




a) feature = HSL
b) feature = Hue
c) feature = Saturation
d) feature = Luminance

Fig. 12. Degrees of intervention of “foreign” paintings for chosen feature (a, b, c, d) for first three artists (black lines) and last three artists (gray lines) from tables 2–5

The first three artists (colored in black lines in graphics) have minimal intervention of "***foreign***" paintings for 3/4 of their pictures.

Speaking in popular terms, the second quartile $Q_j^2$ is the median of the respective characteristic for the respective artist $j$. It shows the value under which are located half of the pictures of this artist and the other half have this characteristic above $Q_j^2$. By looking at these numerical values one may get an impression how the artists are influenced on the "foreign" art. For similar purpose may be used $d_j^{\max}$, as well as the other quartiles.

**4. Conclusions and Future Work.** Digitalization in art work allows the introduction of various numeric expressions of purely qualitative characteristics and elements in the art. In this paper we show the use of the system "Art Painting Image Color Semantics" (APICSS) for image analysis and retrieval.

The obtained result can be used for automatic classification of art paintings in image retrieval systems, where the indexing is based on color characteristics. The system works with JPEG files. The user can choose a desired own populations (we call it groups and form it according to some features) and use this numeric information for analyzing and characterizing some pictures, which can be compared with others from a population. Analysis is based on statistics and descriptive summaries of the obtained numeric information. Then it is easily converted into specific object conclusions and explanations.

Our analyses of a particular painting data base find for example, that there is mixing of color preference by different artist and different movements. Some common, and possibly, still unknown rules can be established. The colors used do not have a normal distribution. The color characteristics in the art are different and in the most cases they represent the artist's style, the scent of his/her time, the movement, the influence of the 'foreign" art.

In our further work we intend to extend the study in two directions. First, using the numerical information generated by art items we intend to develop and attract more statistical tools for analysis of the collected data. Second future development is the use of the existing APICSS for further painting analysis similar to the one illustrated here. We intend to extend the set of observed paintings by including more artists and their work. We will include the Pre-renaissance period, items from East European Orthodox icons, and more Modern art. We will study also different (other) groups formed by the time and country where the painting belongs. We will use the principal component regression analysis [30] to extract the significance of the color use in order to produce rules for search of movements in an image retrieval system.

**Appendix.** Tables 2–5 contain the degree of intervention of "***foreign***" paintings in the zones around the mean vector for pointed artists, bounded by the considering values – quartiles of the distribution of distances "***own***" paintings $Q_j^1$, $Q_j^2$, $Q_j^3$ and $d_j^{\max}$ – the highest distance between the mean vector and the vector from the set of considering group $j$. The artists are sorted by the increasing values of $Q_j^3$.

Table 2. Degree of intervention of "***foreign***" paintings for vectors, containing data for all three characteristics of the color space

| Dist. – HSL<br>Artist | $Q_j^1$ | $Q_j^2$ | $Q_j^3$ | $d_j^{max}$ |
|---|---|---|---|---|
| Giotto | 0.32 | 3.54 | 13.72 | 54.23 |
| Seurat | 2.57 | 6.84 | 15.19 | 43.32 |
| Gauguin | 1.07 | 6.00 | 19.83 | 43.94 |
| Constable | 0.43 | 2.25 | 20.24 | 80.94 |
| Vermeer | 1.07 | 15.01 | 20.47 | 26.80 |
| Cezanne | 3.74 | 11.87 | 21.82 | 77.01 |
| Botticelli | 10.26 | 21.26 | 22.97 | 78.74 |
| Van Eyck | 3.30 | 7.56 | 32.48 | 97.02 |
| Sisley | 8.69 | 21.24 | 33.69 | 84.98 |
| Ghirlandaio | 2.13 | 13.87 | 36.07 | 60.51 |
| Boucher | 5.34 | 27.32 | 37.99 | 48.56 |
| Pissarro | 3.01 | 20.22 | 38.39 | 85.16 |
| Mantegna | 2.66 | 17.36 | 44.83 | 55.70 |
| Titian | 7.82 | 15.74 | 46.68 | 94.54 |
| Poussin | 1.71 | 25.05 | 49.46 | 83.19 |
| Morisot | 14.13 | 23.23 | 50.43 | 79.23 |
| Renoir | 10.41 | 16.31 | 51.29 | 86.16 |
| Filippino Lippi | 5.96 | 23.22 | 51.33 | 58.68 |
| Blake | 9.90 | 31.74 | 51.65 | 81.04 |
| Hogarth | 7.68 | 31.24 | 53.94 | 77.29 |
| Bosch | 9.16 | 26.41 | 53.99 | 63.47 |
| David | 9.54 | 21.65 | 55.20 | 87.03 |
| Monet | 7.30 | 23.28 | 55.26 | 91.31 |
| Van Gogh | 13.81 | 17.13 | 56.00 | 97.22 |

| | | | | |
|---|---|---|---|---|
| Cassatt | 12.83 | 39.04 | 56.36 | 85.78 |
| Piero della Francesca | 1.92 | 37.42 | 57.25 | 82.94 |
| Friedrich | 13.65 | 27.61 | 57.46 | 87.10 |
| Lorrain | 17.22 | 21.18 | 58.29 | 83.64 |
| Steen | 8.15 | 28.22 | 58.80 | 78.65 |
| Raphael | 6.82 | 11.08 | 62.19 | 80.19 |
| Klimt | 16.95 | 30.17 | 62.58 | 80.60 |
| Degas | 35.69 | 51.66 | 63.56 | 76.42 |
| Fragonard | 29.78 | 50.37 | 63.93 | 75.13 |
| Ingres | 8.53 | 38.06 | 64.61 | 86.99 |
| Murillo | 22.52 | 41.41 | 70.86 | 80.47 |
| Courbet | 39.74 | 59.94 | 73.72 | 96.69 |
| Rembrandt | 17.34 | 52.78 | 74.52 | 98.18 |
| Goya | 30.56 | 37.18 | 76.60 | 96.37 |
| Correggio | 5.43 | 15.76 | 77.10 | 82.22 |
| Manet | 14.48 | 38.63 | 77.90 | 89.16 |
| El Greco | 12.54 | 34.51 | 78.14 | 96.14 |
| Corot | 25.16 | 40.04 | 78.80 | 97.54 |
| Velazquez | 56.00 | 63.28 | 81.37 | 99.57 |
| Munch | 18.07 | 33.05 | 81.82 | 99.89 |
| Hals | 21.58 | 77.24 | 84.08 | 98.08 |
| Jordaens | 34.15 | 55.18 | 84.63 | 89.97 |
| Rubens | 8.48 | 23.93 | 95.28 | 100.00 |
| Van Dyck | 48.13 | 68.52 | 95.94 | 96.91 |

Table 3. Degree of intervention of "***foreign***" paintings for vectors, containing data for characteristic Hue

| Dist. – HSL<br>Artist | $Q_j^1$ | $Q_j^2$ | $Q_j^3$ | $d_j^{max}$ |
|---|---|---|---|---|
| Gauguin | 6.32 | 19.94 | 35.16 | 54.56 |
| Sisley | 9.44 | 15.24 | 35.73 | 77.90 |
| Monet | 11.48 | 19.10 | 38.63 | 89.27 |
| Cezanne | 14.65 | 23.64 | 48.24 | 91.02 |
| Botticelli | 17.63 | 27.03 | 53.31 | 73.29 |

| | | | | |
|---|---|---|---|---|
| Morisot | 8.14 | 29.55 | 53.53 | 98.18 |
| Manet | 20.82 | 28.76 | 53.86 | 70.17 |
| Raphael | 17.04 | 32.37 | 56.66 | 86.26 |
| Renoir | 3.43 | 15.67 | 58.69 | 86.70 |
| Correggio | 26.94 | 32.37 | 63.58 | 81.15 |
| Giotto | 44.37 | 48.02 | 63.77 | 79.42 |
| Vermeer | 36.01 | 52.20 | 64.09 | 82.32 |
| Klimt | 10.34 | 32.62 | 64.82 | 85.29 |
| El Greco | 24.01 | 32.37 | 64.84 | 77.60 |
| Lorrain | 9.84 | 31.02 | 69.30 | 93.37 |
| Boucher | 6.08 | 40.45 | 71.08 | 76.95 |
| Blake | 11.40 | 24.60 | 71.46 | 83.71 |
| Bosch | 30.78 | 56.55 | 72.10 | 78.81 |
| Piero della Francesca | 29.85 | 49.89 | 72.49 | 99.79 |
| Pissarro | 23.87 | 44.52 | 73.01 | 94.19 |
| Cassatt | 17.75 | 37.54 | 73.26 | 88.66 |
| Goya | 38.46 | 64.74 | 77.88 | 95.30 |
| Hals | 57.91 | 71.69 | 79.27 | 97.33 |
| Degas | 29.37 | 52.63 | 80.39 | 99.68 |
| David | 38.05 | 59.06 | 80.49 | 95.93 |
| Titian | 45.18 | 63.17 | 80.73 | 89.08 |
| Constable | 26.87 | 46.47 | 80.84 | 98.50 |
| Fragonard | 14.73 | 48.13 | 80.90 | 83.35 |
| Courbet | 32.48 | 59.08 | 80.98 | 89.85 |
| Rubens | 34.66 | 69.21 | 82.73 | 94.10 |
| Hogarth | 65.67 | 68.98 | 82.94 | 96.38 |
| Rembrandt | 30.30 | 61.35 | 85.33 | 89.51 |
| Van Eyck | 45.69 | 52.93 | 86.69 | 94.04 |
| Ghirlandaio | 52.29 | 57.52 | 86.77 | 88.05 |
| Poussin | 49.57 | 76.12 | 88.54 | 90.90 |
| Murillo | 48.24 | 65.10 | 89.43 | 95.94 |
| Corot | 40.04 | 63.28 | 89.72 | 94.65 |
| Van Gogh | 28.16 | 52.46 | 90.26 | 99.36 |
| Van Dyck | 19.10 | 63.61 | 90.39 | 99.47 |
| Ingres | 31.56 | 48.51 | 90.41 | 92.96 |
| Munch | 17.97 | 29.52 | 90.48 | 96.68 |

| | | | | |
|---|---|---|---|---|
| Filippino Lippi | 28.54 | 75.40 | 91.59 | 98.62 |
| Friedrich | 28.89 | 75.80 | 92.00 | 94.99 |
| Jordaens | 37.57 | 67.66 | 92.32 | 95.41 |
| Mantegna | 30.88 | 66.67 | 95.63 | 100.00 |
| Steen | 75.54 | 89.91 | 97.00 | 98.93 |
| Velazquez | 76.23 | 84.48 | 99.04 | 99.89 |

Table 4. Degree of intervention of "***foreign***" paintings for vectors, containing data for characteristic Saturation

| Dist. – HSL<br>Artist | $Q_j^1$ | $Q_j^2$ | $Q_j^3$ | $d_j^{max}$ |
|---|---|---|---|---|
| Vermeer | 6.32 | 13.08 | 22.62 | 67.20 |
| Giotto | 2.25 | 7.82 | 28.40 | 42.12 |
| Cezanne | 13.69 | 24.92 | 35.72 | 88.56 |
| Friedrich | 4.69 | 8.74 | 42.22 | 77.72 |
| Titian | 32.44 | 41.01 | 49.14 | 93.15 |
| Constable | 8.89 | 15.20 | 50.54 | 63.92 |
| Bosch | 22.47 | 27.16 | 52.40 | 63.68 |
| Pissarro | 6.45 | 21.94 | 57.31 | 98.60 |
| Ghirlandaio | 10.46 | 24.55 | 57.63 | 62.22 |
| Van Gogh | 8.35 | 22.16 | 59.21 | 81.37 |
| Botticelli | 21.90 | 34.29 | 62.50 | 88.46 |
| Piero della Francesca | 15.78 | 30.92 | 63.11 | 83.05 |
| Raphael | 27.58 | 41.11 | 63.26 | 70.61 |
| Klimt | 30.70 | 55.01 | 65.35 | 95.10 |
| Gauguin | 10.72 | 19.08 | 67.31 | 78.67 |
| Seurat | 27.49 | 55.19 | 67.49 | 79.79 |
| Hogarth | 31.56 | 62.26 | 70.36 | 92.32 |
| Jordaens | 42.69 | 54.64 | 71.61 | 97.65 |
| Degas | 30.55 | 63.02 | 72.03 | 93.68 |
| Poussin | 35.12 | 55.89 | 73.23 | 88.97 |
| Ingres | 33.26 | 54.80 | 74.09 | 93.28 |
| Boucher | 18.46 | 67.13 | 75.03 | 80.58 |
| Van Eyck | 37.49 | 51.12 | 77.53 | 94.14 |

| | | | | |
|---|---|---|---|---|
| Steen | 54.18 | 72.00 | 78.00 | 90.13 |
| Cassatt | 17.11 | 35.29 | 78.29 | 85.45 |
| Sisley | 30.36 | 49.36 | 78.33 | 90.88 |
| Lorrain | 44.17 | 55.19 | 80.75 | 83.74 |
| Mantegna | 27.37 | 48.88 | 81.79 | 89.56 |
| Filippino Lippi | 24.60 | 41.32 | 81.90 | 86.47 |
| Correggio | 39.72 | 46.01 | 82.22 | 87.11 |
| Manet | 43.45 | 64.38 | 82.40 | 93.78 |
| Monet | 48.93 | 60.41 | 83.91 | 98.82 |
| Hals | 40.81 | 62.18 | 84.19 | 95.83 |
| David | 39.98 | 72.67 | 85.10 | 97.11 |
| Blake | 27.37 | 45.26 | 86.26 | 90.31 |
| Murillo | 65.96 | 69.69 | 86.66 | 90.50 |
| Renoir | 23.18 | 52.25 | 87.66 | 92.81 |
| Goya | 65.06 | 76.28 | 89.10 | 96.69 |
| El Greco | 38.05 | 51.23 | 89.82 | 97.53 |
| Corot | 50.21 | 73.55 | 90.58 | 97.86 |
| Rubens | 11.27 | 30.90 | 91.52 | 99.89 |
| Morisot | 46.47 | 74.84 | 92.51 | 97.22 |
| Rembrandt | 56.96 | 65.74 | 92.61 | 99.79 |
| Courbet | 38.68 | 57.80 | 93.16 | 97.76 |
| Velazquez | 58.24 | 83.51 | 93.68 | 98.72 |
| Fragonard | 54.32 | 72.36 | 94.56 | 98.19 |
| Munch | 26.52 | 66.42 | 96.47 | 99.68 |
| Van Dyck | 46.00 | 66.60 | 97.12 | 100.00 |

Table 5. Degree of intervention of "***foreign***" paintings for vectors, containing data for characteristic Luminance

| Dist. – HSL / Artist | $Q_j^1$ | $Q_j^2$ | $Q_j^3$ | $d_j^{max}$ |
|---|---|---|---|---|
| Giotto | 6.22 | 14.90 | 31.83 | 38.80 |
| Friedrich | 13.65 | 22.49 | 38.06 | 45.10 |
| Constable | 2.57 | 7.17 | 39.29 | 85.33 |
| Pissarro | 15.59 | 24.19 | 40.43 | 83.87 |

| | | | | |
|---|---|---|---|---|
| Ghirlandaio | 13.34 | 20.70 | 45.57 | 77.05 |
| Gauguin | 10.61 | 21.44 | 46.09 | 62.92 |
| Piero della Francesca | 11.83 | 18.23 | 49.79 | 96.48 |
| Cezanne | 10.27 | 34.01 | 51.66 | 88.45 |
| Monet | 20.28 | 28.97 | 52.36 | 97.85 |
| Seurat | 16.15 | 42.14 | 55.51 | 79.89 |
| Morisot | 31.16 | 42.61 | 56.00 | 74.30 |
| Degas | 25.72 | 42.12 | 57.45 | 82.42 |
| Renoir | 17.60 | 43.24 | 58.05 | 88.20 |
| Van Gogh | 8.03 | 44.86 | 60.71 | 98.50 |
| Sisley | 13.41 | 21.89 | 60.94 | 89.81 |
| Filippino Lippi | 21.83 | 51.54 | 62.51 | 78.59 |
| Cassatt | 15.19 | 32.83 | 63.64 | 72.41 |
| Raphael | 14.48 | 29.93 | 65.50 | 93.29 |
| Bosch | 10.76 | 33.76 | 65.92 | 86.90 |
| Mantegna | 27.26 | 37.70 | 68.05 | 68.37 |
| Titian | 23.23 | 52.78 | 68.74 | 93.79 |
| Botticelli | 33.55 | 43.59 | 69.55 | 85.90 |
| Boucher | 25.72 | 50.59 | 69.90 | 84.42 |
| Lorrain | 17.43 | 26.20 | 73.37 | 95.94 |
| Manet | 12.34 | 60.84 | 73.71 | 89.48 |
| Fragonard | 23.16 | 54.96 | 74.17 | 82.82 |
| Klimt | 36.25 | 66.10 | 74.84 | 88.06 |
| Hals | 50.85 | 56.73 | 76.50 | 97.76 |
| Steen | 56.65 | 74.79 | 79.61 | 87.12 |
| El Greco | 32.48 | 66.88 | 80.28 | 93.03 |
| David | 41.16 | 68.17 | 80.71 | 94.32 |
| Goya | 31.20 | 51.07 | 81.73 | 99.79 |
| Blake | 10.97 | 32.16 | 85.41 | 86.90 |
| Ingres | 31.77 | 62.79 | 86.14 | 92.96 |
| Munch | 29.52 | 62.46 | 86.42 | 100.00 |
| Jordaens | 59.55 | 67.88 | 86.66 | 95.73 |
| Rubens | 25.86 | 42.60 | 86.70 | 99.89 |
| Poussin | 53.85 | 77.19 | 87.37 | 94.86 |
| Murillo | 40.77 | 58.16 | 87.51 | 92.53 |
| Correggio | 36.74 | 60.06 | 88.60 | 98.40 |

| | | | | |
|---|---|---|---|---|
| Hogarth | 67.38 | 78.78 | 89.02 | 95.10 |
| Corot | 32.55 | 47.75 | 89.51 | 96.68 |
| Rembrandt | 51.50 | 75.27 | 90.15 | 99.46 |
| Velazquez | 56.00 | 76.34 | 90.26 | 99.04 |
| Courbet | 46.15 | 71.58 | 91.13 | 99.68 |
| Vermeer | 16.29 | 66.45 | 91.32 | 95.28 |
| Van Dyck | 75.99 | 83.99 | 95.94 | 97.76 |
| Van Eyck | 67.73 | 82.43 | 96.17 | 97.44 |

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