SOM BASED ARTISTIC STYLES VISUALIZATION

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ABSTRACT

Painting collections from the old masters are valuable cultural heritage of human history. Their artistic styles can be generally determined by their art periods. From analyzing and visualizing the relationships of different artistic styles, information can be found to facilitate art history studies. In this paper, we propose a Self-organizing Map (SOM) based framework specifically for analyzing and visualizing the relationships among painting collections from artistic perspectives. In our framework, we first define a set of image features based on artistic concepts used in art criticism; then a SOM-based hierarchical model is used to analyze features extracted from individual artists' painting collections. For our experiments, we obtain painting collections of six painting masters representing three art movements: post-impressionism, cubism and renaissance. An interactive web interface is also built to present our artistic influence analysis results. Through our experimental results, styles of different painting collections and their influential relationships can be analyzed and visualized from artistic perspectives.

***Index Terms*—**Artistic styles visualization, Artistic image features, Self-organizing map (SOM)

1. INTRODUCTION

In the domain of art, there is a large body of artistic concepts or principles [8] used for formal critique of paintings. Through evaluating these criterions, artistic styles of different artists and different art movements can be recognized and furthermore the influential relationships among artists can be identified.

With the advances in computer vision, various digital art imaging recognition systems conducting tasks such as painter recognition [20], artistic styles classification [6, 10, 12, 20, 23] have been proposed. However, traditional art imaging systems usually require a large amount of image features computed by image statistics or frequency domain analysis. The meanings of individual features are loosely connected with artistic concepts or principles. Although traditional systems can achieve good recognition results, the results cannot be explained with artistic concepts that are commonly used in the art world. Therefore, it is extremely difficult for them to provide analysis in art influences. Additionally, traditional systems generally do not have good visualization capacity. The relationships among different artistic styles cannot be easily visualized.

To overcome the limitations of traditional art imaging systems, we propose a self-organizing map (SOM) based system specifically for analyzing and visualizing the styles of painting collections from art critics' perspectives. In this work, we make use the advantages of SOM in data clustering and high dimensional data visualization to analyze a set of image features specifically defined based on artistic concepts in art criticism. For our experiments, we obtain a large dataset containing painting collections of six artists representing three art movements: post-impressionism, cubism and renaissance. An interactive web interface is also built to present our artistic influence analysis results. Through our experimental results, the artistic styles of different painting collections and their influential relationships can be analyzed and visualized from artistic perspectives.

The rest of this paper is organized as follows: section 2 briefly reviews related works; section 3 provides an overview of our SOM based hierarchical model; section 4 introduces our artistic concepts based image features; section 5 and section 6 present experiments and discussions of results; finally, our conclusions are drawn in section 7.

2. RELATED WORKS

Previously, several art imaging systems [6, 10, 12, 20, 23] were proposed with a focus on classifying paintings of different artistic styles. However, image features used by [6, 20, 23] were computed through image statistics such as statistics of frequency domain analysis or color histograms in RGB or HSV color spaces, therefore the artistic meanings of features were unknown. Additionally, the relationships of different artistic styles cannot be easily visualized. While most of previous painting classification systems [6, 10, 12, 20, 23] did not address the artistic meanings of extract features, some [5, 15, 22] were developed based on artistic concepts. However, none of them [5, 15, 22] provided a mean to visualize the relationships of painting collections.

Self-organizing Map (SOM) has been widely used in image data clustering analysis and visualization. In general, SOM-based imaging systems [7, 14, 17] are able to provide better visualizations for image data. However, none of the existing SOM-based imaging systems is designed for analyzing painting collections of different painters.

Compared with previous methods, our approach uses SOM to analyze image features of painting collections that specifically defined based on artistic concepts and provides visualization of the relationships among painting collections of different artists. We will further introduce possible applications of our approach in section 5.2.

3. OVERVIEW OF OUR APPROACH

Self-organizing map (SOM) [13] is a sheet-like unsupervised neural network model which consists of a regular lattice of neurons in hexagonal or rectangular topology. Through an unsupervised learning process, neurons of SOM can be specifically trained to represent and visualize high dimensional input patterns on a two-dimensional grid. Because of its ability in data clustering, multi-dimensional scaling and information visualization, SOM has been widely used in various data analysis, pattern recognition and visualization applications.

In this work, we propose a two level SOM-based hierarchical model for analyzing images of paintings. Fig. 1 illustrates our proposed model. Due to the variability of paintings, it is common for one painter whose artworks may represent one single school of art (such as impressionism) to develop several minor different styles throughout life time (due to the use of different techniques, lightings or color schemes). Therefore, features of painting collections from different artists are processed by separate SOMs in the first level of our model (see Fig. 1) to first find clusters and reduce outliers within each painting collection. Since SOM can achieve vector quantization and dimension reduction at the same time, image features of each painting collection can be represented by a small number of prototype vectors (i.e., winning neurons of individual SOMs in the first level). Then, in the second level, the prototype vectors that represent each artist's painting collection can be used to train another SOM for artistic style clustering purpose. Details of our proposed model will be introduced with our experimental results in section 5.

4. IMAGE FEATURE EXTRACTION

4.1. Color

"*Visual temperature of color*" which indicates the feel of warmth or coldness of color is often used as an important criterion to analyze colors in paintings. Through using colors of different temperatures (cold or warm), different emotions can be expressed. We define "*Hue temperature score*" by using the wavelengths of the visible color light waves (for its relation to temperatures of color light waves) to interpret this concept [21].

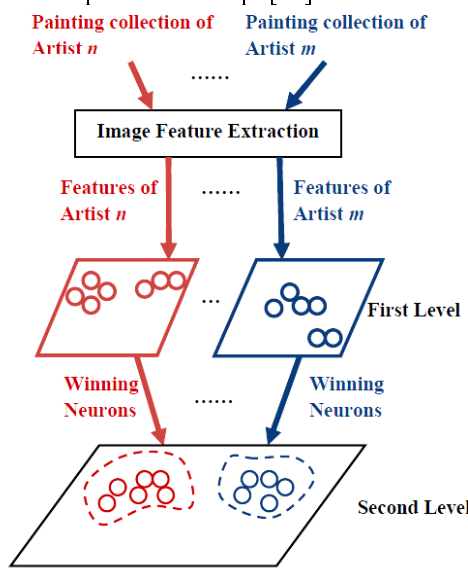


Fig. 1. Our proposed SOM-based hierarchical model.

"Visual weight of color" indicating the feel of heaviness of color is another criterion in assessing colors in paintings. "Heavy colors" (such as dark colors) can be used to produce a sad or solemn atmosphere in paintings. Studies in psychology [18, 19] found that lightness of color has an important effect on color weight, i.e. darker color appears heavier and brighter color appears lighter; however, the effect of saturation on color weight varies among individuals. Through experiments in color psychology, [18] also concluded the ordered sequence (from heavy to light) for the visual weight of pure colors (or hues): Blue, red, green and yellow. In this work, we define the visual weight of colors as a function of hue and lightness in CIE LCH color space. Weight of different hues (such as blue, red, green and yellow) and weight of different levels of lightness (such as black, gray and white) are both considered. In our model, the visual weight of different hues and lightness are considered to follow the sequence <u>(start from the heaviest): black, blue, red, gray, green, yellow and white</u>. We first linearly assign a weight score ranging from 1 to 0 (1 denotes the heaviest, 0 denotes the lightest) to each of above seven categories of colors. Then we use polynomial curve fitting to find relations between the assigned weight scores and hue values of blue, red, green, yellow; and exponential curve fitting to find relations between the assigned weight scores and

lightness of black, blue, red, gray, green, yellow, white. Finally, the overall weight score of a color is defined as a weighted sum of its hue related weight score and its lightness related weight score. Fig. 2 plots the color weight scores in Cartesian coordinates for entire color ranges in CIE LCH space (hue values range from 0 to 360 degrees and lightness values range from 0 to 100). In the plot, weight scores of colors in CIE LCH space form a surface; the closer the score to 1, the "heavier" the color is.

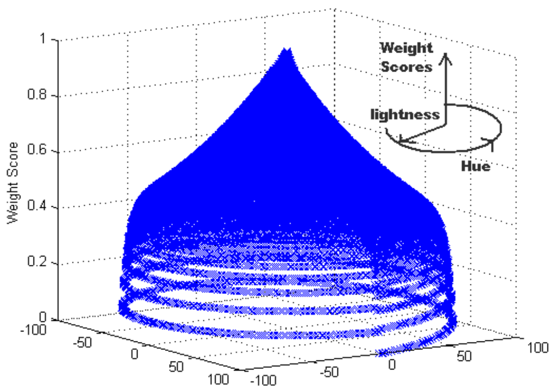


Fig. 2. Color weight scores of entire color range.

4.2. Composition

To interpret composition principles, we make use of Itti and Koch's saliency model [11]. It was proved by [9] to be suitable for predicting fixations for different genres of paintings. For each image of painting, we compute a saliency map of the same size to encode visual salience in each pixel. Then the saliency map is divided into thirds both horizontal and vertical wise and compute the mean salience for each of the nine sections to interpret "rule of thirds". Additionally, properties of the most salient region such as "size", "symmetricity", "rectangularity" and "most salient point" are used to represent properties of "golden section" composition principles. Refer to [21] for intermediate results and detailed definitions.

4.3. Lines

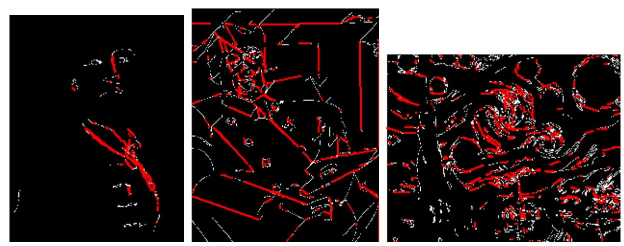
Lines in paintings are generally perceived as edges. Different styles of paintings or different painters may favor a certain type of lines. To interpret the concepts of lines, we use Hough Transform to find straight lines that are above a certain threshold in a painting. And then we calculate the mean slope, mean length, and standard deviation of slopes of all the detected straight lines. Fig. 3 shows an example of different line properties in different styles of paintings. Canny edge detector and Hough transform are used to find straight lines that are longer than 10 pixels. Fig. 3 shows the slopes and lengths of detected straight lines vary in renaissance and cubism paintings.

4.4. Summary of Features

37 numeric features are defined to represent artistic concepts in color, composition and lines. All the features are numeric number ranging from 0 to 1. Artistic concepts used for defining our image features are summarized in Table 1.

Table 1. Summary of selected image features

Categories	Artistic Concepts [8]	No. of Numeric Features
Color	Visual temperature of color [21]	4
	Visual weight of color	4
	Expressiveness of color [21]	10
Composition	Rule of thirds	10
	Golden section	5
Lines	Different types of straight lines	4



(a) Renaissance (b) Cubism (c) Postimpressionism

Fig. 3. Detected straight lines in different styles of paintings. Straight lines are indicated by red color.

5. EXPERIMENTS

5.1. Image Data

Our image data of paintings are available for download at: http://sourceforge.net/projects/sombasedpaintin/files/. All the painting images are collected from various Web-based resources[1, 2]; therefore they vary in size and resolution. 663 paintings from six artists representing three different art movements are collected (Table 2). Due to the complex nature of paintings, even one artist may develop different painting techniques and styles from time to time. Therefore, for each artist, we try to ensure the selected paintings cover a wide range of techniques and subjects; also ensure they were painted during different periods of the artist's life.

Table 2. Details of collected image data

Artists	Art movements	No. of paintings
Van Gogh	Postimpressionism	137
Gauguin		136
Braque	Cubism	114
Gris		117
Raphael	Renaissance	67
Titian		92

5.2 Clustering Analysis of Painting Collections

We propose a two level hierarchical SOM model (see section 3) for clustering analysis of paintings. The final result of clustering can be visualized through hit histograms which indicate the distributions of best matching units (BMUs) of data on a SOM.

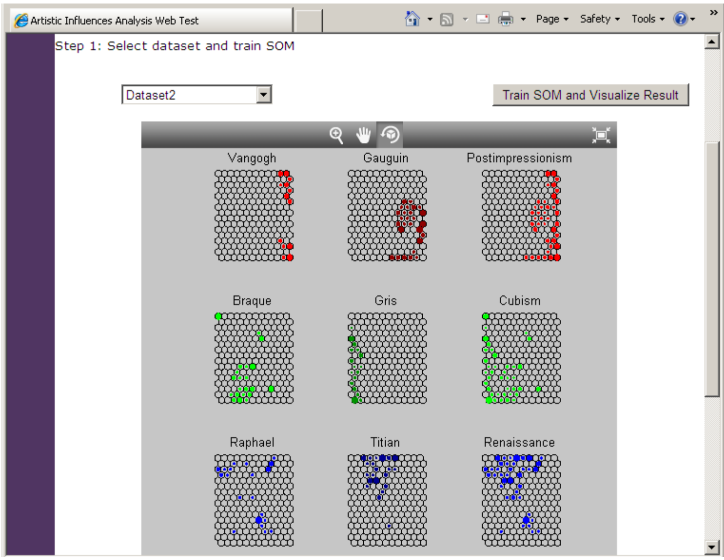


Fig. 4. Artistic style visualization web interface. Hit histograms of six painters' painting collections on the 2nd layer of the hierarchical SOM model are shown. The hit histograms in the right most column combine histograms from the other two columns to show clustering result of different art movements.

In Fig. 4, hit histograms of 6 painters' painting collections representing three art movements are shown. The analysis of such clustering result from different aspects can be used for various applications. We will further introduce three different applications in details.

5.3. Comparisons of multiple painting collections

Relationships among painting collections of different painters can be analyzed through comparing the final prototype vectors (Fig. 4) of each painter. From visual inspection of Fig. 4, we can see that the BMUs of painters belonging to the same art movement tend to locate at neighboring map units indicating their high similarities in the feature space. The quantitative comparisons of painting collections can be done by taking some distance measure (such as Euclidean distance) among the centers of final prototype vectors, and then hierarchical clustering is applied (Fig. 5). The average Euclidean distance in Fig. 5 indicates dissimilarities among each painting collection in the feature space. We can see that painting collections of the same art movements are much more similar to painting collections of different art movements. Among three art movements, postimpressionism is closer to renaissance than cubism in feature space. This could be explained by different time periods of three art movements (renaissance being the earliest, cubism being the latest). Also cubism, different from postimpressionism and renaissance, is a form of abstract art which does not directly depict reality.

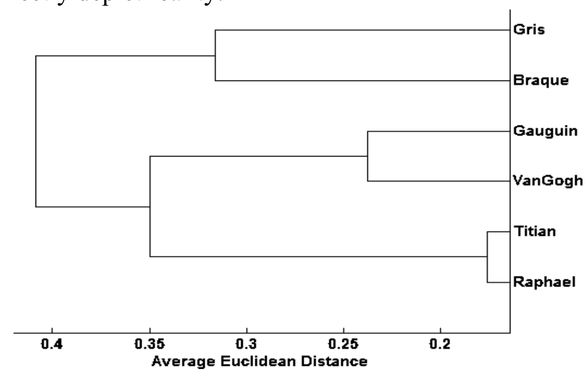


Fig. 5. Comparisons of six painter's painting collections

5.4. Comparisons within a single painting collection

Standard deviations of final prototype vectors of each painting collection can be calculated to assess the variation of styles (in terms of color, composition and lines in the feature space) within one painting collection. In Fig. 6, we can see that Van Gogh and Raphael's collections have the largest variations in styles. To get a better visual inspection of variations within one painter's collection, paintings from two separate clusters of Van Gogh's collection are shown in Fig. 7. Clearly, they represent two "minor-styles" within Van Gogh's painting collection, which could be explained by different lighting techniques used in these paintings. As for the variation in Raphael's painting collection, this is because we include fragments of Raphael's large fresco paintings (typically painted on the roofs and walls of churches, e.g. "The School of Athens" [3]) in our dataset. Due to different painting surfaces, fresco paintings usually have different visual appearance in color from oil paintings on canvas.

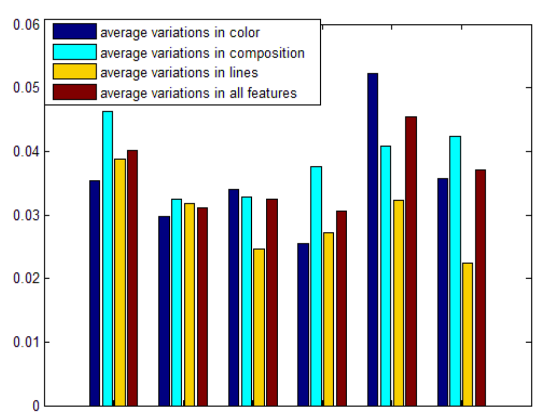


Fig. 6. Style variations within each painting collection.

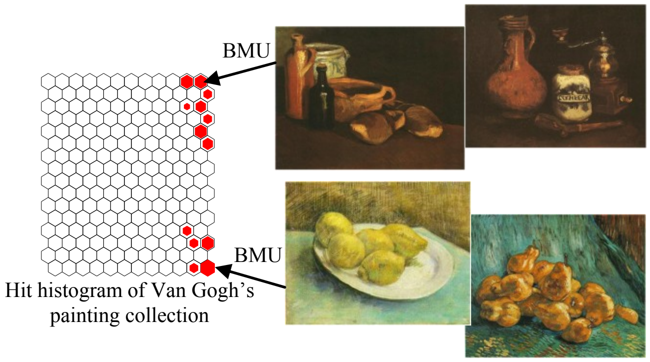


Fig. 7. Variations of styles within Van Gogh's collection. The best matching units (BMU) of given paintings are located in two separate locations of the hit histogram.

5.5. Artistic influential analysis of paintings

Art studies are particular interested in discovering the art influences of paintings. In our system, this can be done through first finding the BMU of a given painting on a trained SOM, then similarities (indicating influential relationships) between prototype vectors that representing different artistic styles and the given painting can be measured. In Fig. 8, one of Picasso's cubism paintings (not included in the dataset) is uploaded by the user through our web based interface. The BMU of the uploaded painting is found to locate within Braque's cluster (light green). Then Braque's painting found to be most similar to the uploaded painting is shown next to the trained SOM. Since Picasso is considered as the inventor of Cubism, and Braque being another founder of Cubism, their influences on each other are unavoidable.

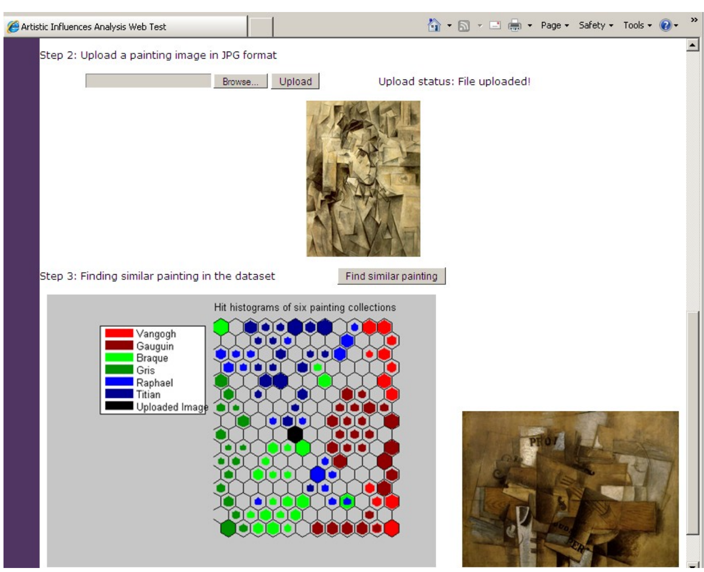


Fig. 8. Artistic influence analysis. One of Braque's paintings is found to be most similar to the uploaded Picasso's painting.

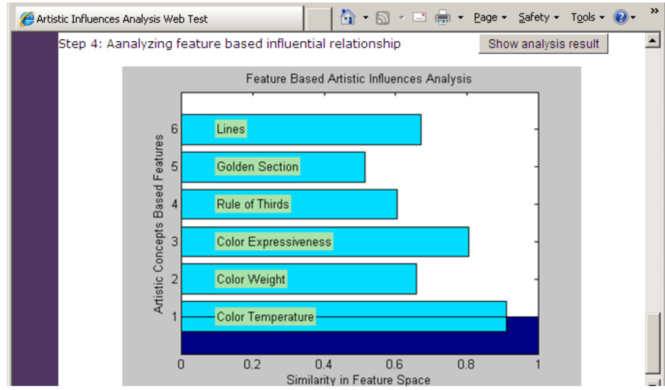


Fig. 9. Artistic influence analysis in terms of artistic concepts between the uploaded Picasso's painting and the found Braque's painting in Fig. 8.

Influences in terms of various artistic concepts (such as "color temperature") can be also analyzed based on extracted artistic features (see Table 1). Fig. 9 shows such analysis result through our web interface. It indicates the uploaded Picasso's painting has an influential relationship with the found Braque's painting in "color temperature" and "color expressiveness" and "lines", which is coherent with our visual inspection and knowledge in art history[4]. Another result of artistic influential analysis is shown in Fig. 10. Picasso's painting "La Celestina" is found to be influenced by Titian's Renaissance painting (Fig.10) in terms of composition rules and line styles. This result is also coherent with our visual inspection.

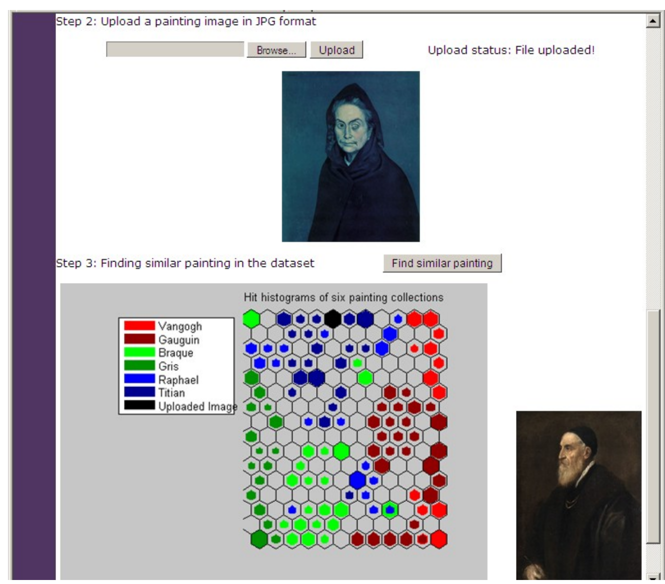


Fig. 10. Another result of artistic influence analysis. Picasso's blue period painting "la celestina" is found to be influenced by Titian's painting in "golden section", "rule of thirds" and lines.

5.6. DISCUSSION

As far as the authors are concerned, our work is the first that uses SOM-based data clustering approach to analyze and visualize the influential relationships among paintings. Previous related works mainly focus on painting styles classification. They usually use relatively small dataset and do not have good visualization capacity. In this section, we compare our work with previous most related works [16, 20]. From Table 3, we can see that our system is designed more intuitively in terms of artistic meanings. Therefore it is much more suitable for art influence analysis from art critics' perspectives. More importantly, with SOM, our approach offers better visualizations of our analysis results. In summary, our proposed framework provides new means of artistic styles analysis and visualization.

Table 3. Comparison between our work and previous works

	Shamir et al. [20]	**Lombardi [16]**	**Our work**
Image features	11 statistic based feature extraction algorithms	Statistic features modeling light, line , texture and color	Artistic features defined based on concepts in art criticism
No. of features	3658	57	37
Artistic meanings of features	No	Has generic meanings, but no detailed meanings	Yes
Image data size	513 paintings of 9 painters from 3 art movements	60 paintings of 6 painters from 2 art movements	663 paintings of 6 painters from 3 art movements
Data clustering method	Phylogeny tree	K nearest neighbor; Hierarchical clustering; SOM	SOM-based hierarchical model; Hierarchical Clustering
Visualization	Difficult	Not explored	Easy
Applications	Artistic styles classification, painter recognition	Artistic styles classification	Analysis and visualization of Artistic styles and influences

6. CONCLUSION

In this paper, we proposed a SOM-based model for analyzing and visualizing the relationships among painting collections of different painters from artistic perspectives. The experiments demonstrated our approach can be used in various applications including comparisons of multiple painting collections, comparisons within a single painting collection and artistic influences analysis.

In the future, we would like to further seek art expert opinions, conduct comprehensive user studies through our web-based interface, which can be used to improve our system.

7. REFERENCES

[1] Web Museum. http://www.ibiblio.org/wm/.

[2] The Artchive. http://www.artchive.com/.

[3] The School of Athens. http://en.wikipedia.org/wiki/The_School_of_Athens.

[4] The Artstory.org--George Braque. http://www.theartstory.org/artist-braque-georges.htm.

[5] Corridoni, J. M., del Bimbo, A. and Pala, P. Retrieval of paintings using effects induced by color features. *Content-Based Access of Image and Video Database, 1998 IEEE International Workshop on*, 2-11, 1998.

[6] Culjak, M., Mikus, B., Jez, K. and Hadjic, S. *Classification of art paintings by genre*. City, 2011.

[7] Deng, D. *Content-based comparison of image collections via distance measuring of self-organised maps*. City, 2004.

[8] Fichner-Rathus, L. Foundations of art and design. *Wadsworth Pub Co*, Boston, MA, 2012.

[9] Fuchs, I., Ansorge, U., Redies, C. and Leder, H. Salience in Paintings: Bottom-Up Influences on Eye Fixations. *Cognitive Computation*, 3, 25-36, 2011.

[10] Gunsel, B., Sariel, S. and Icoglu, O. Content-based access to art paintings. *Image Processing, 2005 IEEE International Conference on (ICIP 2005)*, 2, II-558-561, 2005.

[11] Itti, L., Koch, C. and Niebur, E. A model of saliency-based visual attention for rapid scene analysis. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 20, 1254-1259, 1998.

[12] Jia, L. and Wang, J. Z. Studying digital imagery of ancient paintings by mixtures of stochastic models. *Image Processing, IEEE Transactions on*, 13, 340-353, 2004.

[13] Kohonen, T. The self-organizing map. *Proceedings of the IEEE*, 78, 1464-1480, 1990.

[14] Laaksonen, J., Koskela, M. and Oja, E. PicSOM: self-organizing maps for content-based image retrieval. *Neural Networks, 1999. IJCNN '99. International Joint Conference on*, 4, 2470-2473 vol.2474, 1999.

[15] Leslie, L., Chua, T.-S. and Ramesh, J. Annotation of paintings with high-level semantic concepts using transductive inference and ontology-based concept disambiguation. *Proceedings of the 15th international conference on Multimedia*, 443-452, 2007.

[16] Lombardi, T. The Classification of Style in Fine-art Painting. *Dissertation, Pace University*, 2005.

[17] Marinai, S., Marino, E. and Soda, G. Transformation invariant SOM clustering in Document Image Analysis. *Image Analysis and Processing, 2007. ICIAP 2007. 14th International Conference on*, 185-190, 2007.

[18] Marion, M. The Apparent Weight of Color and Correlated Phenomena. *The American Journal of Psychology*, 36, 192-206, 1925.

[19] Payne, M. C., Jr. Apparent Weight as a Function of Color. *The American Journal of Psychology*, 71, 725-730, 1958.

[20] Shamir, L., Macura, T., Orlov, N., Eckley, D. M. and Goldberg, I. G. Impressionism, expressionism, surrealism: Automated recognition of painters and schools of art. *ACM Trans. Appl. Percept.*, 7, 1-17, 2010.

[21] Wang, Y. and Takatsuka, M. A Framework towards Quantified Artistic Influences Analysis. *Digital Image Computing: Techniques and Applications (DICTA'12)* 2012.

[22] Yelizaveta, M., Chua, T.-S., Irina, A. and Jain, R. Representation and retrieval of paintings based on art history concepts. *Multimedia and Expo, 2004 IEEE International Conference on, (ICME '04)*, 2, 1023-1026 Vol.1022, 2004.

[23] Zujovic, J., Gandy, L., Friedman, S., Pardo, B. and Pappas, T. N. Classifying paintings by artistic genre: An analysis of features &classifiers. *Multimedia Signal Processing, 2009. MMSP '09. IEEE International Workshop on*, 1-5, 2009.