Colors in Art History what can the colors of a painting tell about it's time context?

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Abstract. *Art creation and analysis is one of the most human specific activities existent. The creative process, emotions, thoughts and special circumstances of the artist are just a few factors that can influence the final result of an art piece. Still, in art history it is possible to recognize patterns regarding techniques and materials, when comparing artist of the same movement or context. Every time a new pigment is discovered, for example, we see an explosion in it's use on the next years. For this reason, in this paper we are going to study the correlation between the use of color and the time frame paintings were produced. The objective of this work is to use computer vision algorithms to try to draw a pattern for that relationship through human history.*

1. Introduction

Every person who has been to a museum, art exposition or had arts lectures at school or university has been presented to the concept of art movements. In a specific time and place, a group of artists create paintings, sculptures, drawings... in a specific pattern, identifying that period as something unique, separate from what has been and what will afterwards be. It is common for us to correlate art pieces by their aesthetics and try to infer about the context it was created based on those features. Yet, it seem hard for most people to put into exact words what are their criteria and how much they are supposed to make sense in the bigger scale. As this process is so uniquely human and so connected to our emotions and previews knowledge it is for sure an interesting topic to be studied in terms of computational methods. How can we approximate arts analysis through emotionless algorithms and image processing?

A starting point to solve this problem is analysing the features we can easily formalize into text, for example shapes, materials, colors, size, and from there build more robust and detailed algorithms. Therefore, here we are going to isolate the factor color from paintings and begin this journey towards human experiences.

In this work three external sources were used:

1. SemArt Dataset from Aston University Library Service: collected from the Web Gallery of Art (https://www.wga.hu/) is a corpus with 21,384 samples that provides artistic comments along with fine-art paintings and their attributes for studying semantic art understanding. This dataset was used as the base of learning. The 10 main colors (RGB) of each painting were extracted as a base for the correlations.

2. Art Images: Drawing/Painting/Sculptures/Engravings from Kaggle: about 9000 images containing Drawings, watercolors, paintings, sculptures. In this paper we extracted only the paintings and used them as input to have their colors (RBG) correlated with the images from SemArt.

3. Codebrainz/Color-Names: csv availabe on github with 856 RGB - hex color correspondences. It was used to translate the extracted RBGs into a more concise and human readable information pattern.

2. Related work

(Garcia, Renoust, Nakashima, 2018) introduced SemArt dataset. To evaluate semantic art understanding, they envisage the Text2Art challenge, a multi-modal retrieval task where relevant paintings are retrieved according to an artistic text, and vice versa. They also propose several models for encoding visual and textual artistic representations into a common semantic space. Their best approach is able to find the correct image within the top 10 ranked images in the 45.5 percent of the test samples. Moreover, their models show remarkable levels of art understanding when compared against human evaluation.

(Bartz, Jain, Krestel, 2020) propose an approach to retrieve the associations between images and texts for artworks from art-historic archives. They use machine learning to generate text descriptions for the extracted images on the one hand, and to detect descriptive phrases and titles of images from the text on the other hand. Finally, they use embeddings to align both, the descriptions and the images.

3. Methods

The method used consisted in two phases, pre-processing and running operation:

1. Pre-processing: Identifying base artworks and their colors: Extract the 10 main RBG patterns in every painting in SemArt. Translate each RGB set into a hex code and save it all in a table.

2. Running operation:

   Identifying input image colors: Extract the 10 main RGB patterns of target image. Translate each RGB set into hex code.

   For each image in the pre-processed table, extract all that have common colors with target image.

   Select 10 images with the highest amount of common colors regarding the target image (10 nearest neighbours).

   Plot distribution of creation years of the nearest neighbours regarding the number of common colors accumulated in that period.

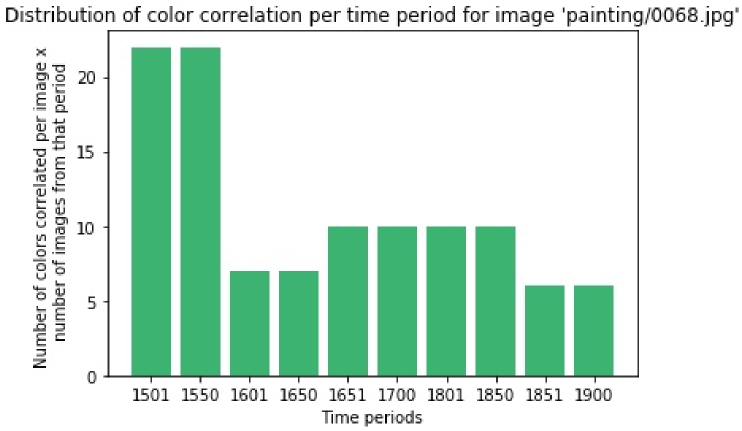
4. Experiments and Results

After the final step the user views a graph with the distribution and can interpret the most probable period of creation for that painting. Two main patterns were recognized in this phase: the art piece was either part of a medium-high plato period of the distribution (that means, not the peak period, but a relatively high and extended related period), or part of a peak. For older paintings (before 1850) the first pattern was recognized more often, while for more recent paintings (after 1850) the second one was more frequent.

Examples:

In figure 01, Peter the Great (1672-1725), we can perceive the plato pattern, as between 1650 and 1850 the color relationship between this painting and our database scored 10. The peak of 1501 - 1550 does not relate to the actual situation of the artwork.

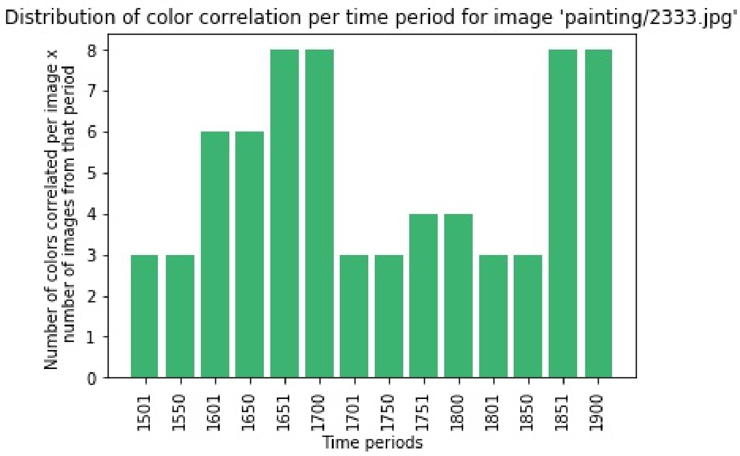
(a) Peter the Great (1672–1725)



(b) Graphic generated for figure 1(a)

Figure 1. Example 01

(a) Youth. Morning - Arkady Plastov (1953-1954))



(b) Graphic generated for figure 2(a)

Figure 2. Example 02

In figure 02, Youth. Morning, from Arkady Plastov (1953-1954), we can perceive the peak pattern, but still not very precisely. This image had a fairly uniform color correlation for almost 400 years, peaking both around 1650 and 1900, which are not exactly the time frames we are looking for.

5. Conclusion and Future Work

Analysing this work and both papers presented at the ”Related Works” section it is possible to realise that the automated art analysis field is still mostly unexplored. Based on the results acquired here the conclusion is drawn into the direction of opening space for future work. A good approach would be exploring the shapes and crossing that information with the already acquired color database.

The developed code and generated files can be found at

https://github.com/vieira-giulia/ColorCorrelationInArtHistory/

A series of videos explaining this project can be found at

https://www.youtube.com/playlist?list=PL9XyeocFYR9bmwS-XJ7BGRebPpB3Jqj1N/

6. References

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