Unsupervised Clustering for the Chronological Analysis of Digitized Paintings

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Abstract: **In this study, unsupervised clustering techniques are applied to digitized paintings of two famous Pointillist artists, Paul Signac and Georges Seurat. That way we temp to reveal natural division of each artist oeuvre into different time periods and moreover to unlock the features that mostly contribute to the shaping of clusters and thus to conclude the evolution of the artistic styles adopted by the painter over time. A large set of engineered features is used and the feature ranking process identifies the most important features: run-length features, fractal dimension, and statistical features derived from hue histograms. Interpretation of the analysis of the most important features shaping the clusters in terms of painters' style evolution is consistent with evidence of art experts.**

Keywords: **Digital cultural heritage, Painting analysis, Unsupervised Clustering.**

I. INTRODUCTION

The extensive digitization of artworks has been accompanied by interest in the use of machine learning techniques for their semantic processing. Recent related research explores the use of engineered features [1-3], convolutional neural networks [4-8], and transfer learning [9-11] for tasks such as authentication, analysis and artworks classification.

The use of unsupervised techniques contributes to the identification of underlying structures in artistic works without the need for predefined labels. In this direction, research was conducted for selecting representative artworks [12], performing art analysis tasks such as discovering influences between artists, identifying different periods within a single artist's production [13-16], and clustering artworks into appearance-based groups [17].

In this study, we use clustering techniques to detect the existence of inherent temporal groupings in the paintings of two famous Pointillist artists, Georges Seurat and Paul Signac. Art historians generally recognize a development in Seurat' style over his relatively short career, shaping two artistic periods. His early works show an influence from traditional Impressionist movement. Around the mid-1880s, (especially after 1884-1885), Seurat evolved his style towards a more structured technique, exemplified by masterpieces like Sunday Afternoon on the Island of La Grande Jatte (1884–1886), creating the Pointillism artistic movement [18, 19]. Similarly, based on Signac's art curators, three loose artistic periods can be distinguished in his career. Signac in his early works was mainly influenced by the Impressionist movement, but soon his acquaintance with Seurat and his Pointillist artworks would turn him towards adopting the Pointillist technique. After Seurat's early death, he would also become the main supporter of the movement, "a tireless and talented promoter" of Pointillism [20, 21]. During these pivotal years, his work appears to be morphologically very coherent. In his last years, and especially after his move to Antibes (1913), his works became more expressive, relaxing his adherence to the discipline of Pointillist techniques. Figures 1 and 2 illustrate characteristic artworks corresponding to the assumed chronological periods of Seurat and Signac, respectively.

The digitized works used in the research to identify these chronological phases came from the WikiArt Visual Art Encyclopaedia, [22]. Initially, transfer learning technique is used, which confirmed the existence of temporal clustering of the artists' works. However, the lack of interpretability of the results led to the use of engineered features and Agglomerative Hierarchical Clustering to reveal the artistic choices that differentiate the works of each group. Statistical analysis of the most important features, resulting from feature ranking procedure, allows to trace stylistic evolution in artists' oeuvre during time.

The paper is organized as follows. Section 2 describes the dataset. Section 3 presents the transfer learning experiment. Section 4 introduces the engineered features and clustering methodology. Section 5 concludes the paper.

a b

Fig. 1: a: Part of Impressionist painting of Georges Seurat "Peasants Driving Stakes" (1882), b: Part of Pointillist painting of Georges Seurat "Sunday Afternoon on the Island of La Grande Jatte" (1884-1886). Public domain artworks acquired by https://www.wikiart.org/.

a b c

Fig. 2: a: Part of Impressionist painting of Paul Signac “Still Life with a Book” (1883), b: Part of Pointillist painting of Paul Signac “Capo di Noli” (1898), c: Part of Watercolor of Paul Signac “Rodez” (1923). Public domain artworks acquired by https://www.wikiart.org/.

II. DATA SET

Two datasets were constructed using digitized paintings retrieved from WikiArt. The first dataset consists of 129 paintings by Georges Seurat, selected from 179 available in WikiArt collection, excluding artworks made with pencil. Artworks were registered in 12 catalogues based on the date of their creation (from 1879 to 1891) according to WikiArt labelling. The second dataset includes 83 paintings by Paul Signac, selected from 101 available works after excluding undated works and a few pencil sketches. The artworks are organized into catalogues according to their year of creation, ranging from 1882 to 1935, resulting in 37 catalogues.

In both datasets, the number of paintings per catalogue varies. For practical reasons, catalogue labels were encoded as ordered numerical indices, where lower values correspond to earlier works and higher values to later works. Digitized paintings are pre-processed and then used for features extraction.

III. CLUSTERING WITH TRANSFER LEARNING

As a first step, we employed transfer learning to explore potential inherent groupings in each dataset. Specifically, we used the pre-trained AlexNet convolutional neural network and extracted features from the ReLU-7 layer. Input images are resized to 227 by 227 by 3 to match the required input size for AlexNet. Due to the high dimensionality of the extracted features (4096-dimensional feature vector), Principal Component Analysis (PCA) was employed for dimensionality reduction and visualization.

Initially, transfer learning is applied to the digitized artworks of Seurat. Fig. 3 depicts the graphical representation of the three top principal components result from the PCA. The true classes are assumed to be the years of artworks creation, as explained in the previous section. Since the number of true classes is numerous, the labels of the points are omitted and instead information about the label is given by the chromatic map of the heatmap. From the figure we can observe that there is a grouping of works belonging to the early years (cyan shades) and a second one that includes the remaining works of the later years (magenta shades). Black coloured circles are added to the scattering diagram to roughly indicate the assumed clusters.

In the case of Signac's artworks, the same procedure was followed. Fig. 4 represents the scattering diagram of the three top principal components resulted from PCA. Having in mind the shaping of meaningful clusters in terms of time periods, that is clusters containing, as much possible, consecutive years, three clusters can be considered, corresponding to early years (cyan shades), mid years (blue shades) and late years (magenta shades). Again, black coloured circles are added to the scattering diagram to emphasize the assumed clusters.

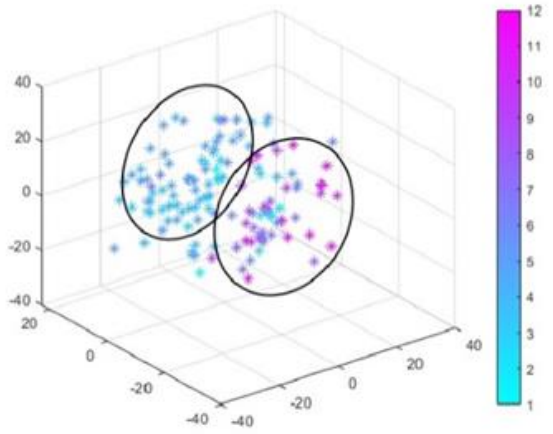

Fig. 3: 3D visualization of clusters formed from features extracted using AlexNet with transfer learning, applied to Seurat’s paintings. Dimensionality was reduced using PCA, and the plot shows the three principal components. Colors correspond to painting dates, as indicated by the accompanying heatmap. Two highlighted circles mark clusters that align meaningfully with chronological divisions in Seurat’s work.

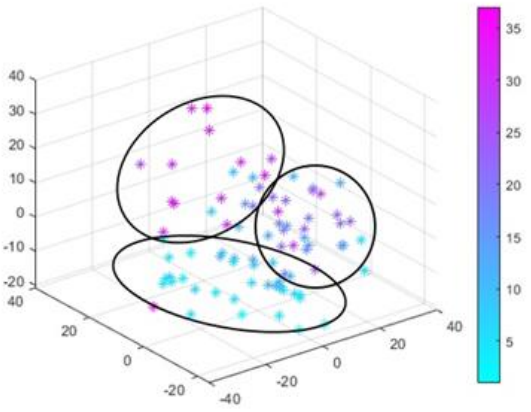

Fig. 4: 3D visualization of clusters formed from features extracted using AlexNet with transfer learning, applied to Signac’s paintings. Dimensionality was reduced using PCA, and the plot shows the three principal components. Colors correspond to painting dates, as indicated by the accompanying heatmap. Three highlighted circles mark clusters that align meaningfully with chronological divisions in Signac’s work.

IV. CLUSTERING WITH ENGINEERED FEATURES

Deep neural networks are powerful tools for classification tasks however, their results are not interpretable by humans [23]. The experiments described in the previous section, indicate a chronological division in the oeuvre of the two artists, but, results cannot be interpretable in terms of the qualitative delimitation of the clusters. To address this inefficiency, we employed engineered features, allowing for more transparent analysis. A wide range of features was initially examined, and through experimentation, a specific subset emerged as having the most significant impact on the clustering process. The general procedure followed is outlined below.

The employed features extracted from the data set are: Run Length features [24], texture and colour features proposed in [25], a set of statistical features derived from the hue, saturation and value channels histograms (mean, standard deviation, energy, entropy and skewness), colour redundancy metric [2], Hausdorff fractal dimension [23], [26], blob-based shape features from binarized grayscale images (mean and standard deviation of the equivalent diameter of the blobs, number of blobs, average eccentricity of blobs), edges statistics features and Gabor filters features [1].

To identify clusters of paintings indicating different time periods in artist oeuvre, the hierarchical clustering technique was employed. The adopted number of clusters was determined by hierarchical clustering using Ward's linkage method on the pair-wise Euclidean distances between features vector. The silhouette method was then employed to evaluate clustering quality across a range of cluster numbers. For each value of clusters number (from 2 to 10), the average silhouette score was computed, and the number of clusters corresponding to the highest silhouette value was selected as optimal. To assess feature contribution, statistical analysis using ANOVA was conducted. Features exhibiting significant inter-cluster differences were ranked as more influential in chronological separation.

A. Description of the most important features

The most important features in either case (Seurat or Signac) are briefly described here, emphasizing their interpretative value with respect to the visual attributes under-lying the clustering structure.

Run Length Features. Run length features characterize the textural patterns within images, reflecting brushstroke structure and the visual complexity of the paintings. Among the run length texture measures [24], the most relevant for the clustering process are High Grey-Level Run Emphasis (HGRE), Short Run Emphasis (SRE), Long Run Emphasis (LRE), and Run Percentage (RP).

Mean of gradient magnitudes across the image. The gradient coefficient calculated from the gradient map of the painting image [25], is used to identify regions of the image with a significant change in intensity and reflects the overall structure in the artwork.

Hausdorff fractal dimension. The Hausdorff fractal dimension (HFD) of an image provides a numerical measure of its visual complexity and texture density. To quantify the fractal content of the painter's artworks, the box-counting method was applied.

Number of Edges. The Roberts method is used for edges detection and then the number of edges of the image is calculated. This feature can be interpreted as an indicator of the composition's complexity—higher edge density suggests finer brush-work, greater textural richness, whereas fewer edges imply softer transitions and a more uniform surface.

Entropy in the hue channel histogram. The entropy in the histogram of the hue channel is translated to a quantitative measure of the randomness and unpredictability within an artwork's visual composition [27]. Higher hue entropy is related to more informational and complex paintings, while lower hue entropy suggests more predictable and harmonious colour expression in the paintings.

B. Seurat

Initially, the case of Georges Seurat was investigated. Based on the feature vector extracted from the paintings, hierarchical clustering was performed and the clustering of the artworks in two time periods was established, one corresponding to works created before 1885 (true class 6) and another corresponding to his later works (after 1885), as shown in the heatmap of Fig. 5. There is no tight separation between the clusters that were produced across various time periods. Because artists may return earlier styles without clearly defined borders between periods, chronological separation is not absolute, which is why this overlap is expected.

Feature ranking identified the most important features in the clustering process: mean gradient magnitudes, Run Length features, Fractal number, and edge statistics.

Boxplot analysis of the most important features is employed to outline the main characteristics of the two periods. For example, gradient magnitudes (Fig. 6a) increase from class 1 to class 2, indicating a transition from looser to more defined and systematic brushstrokes. Similarly, SRE (Fig. 6b) reflects the change from early, impressionistic works to a more structured pointillism in the later years.

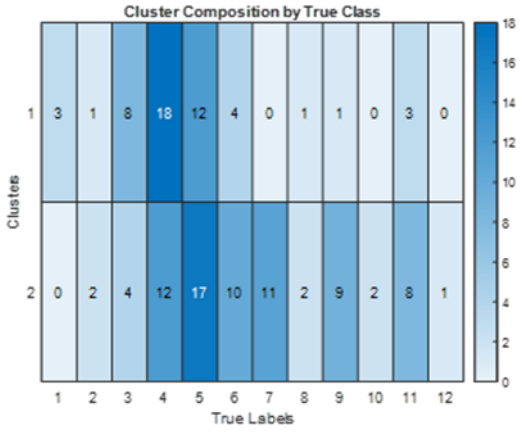

Fig. 5: Heatmap showing the composition of the two clusters formed from engineered features of Seurat's paintings, in terms of their true chronological labels. The true labels correspond to the year of each painting's creation, ranging from 1 (1879) to 12 (1891).

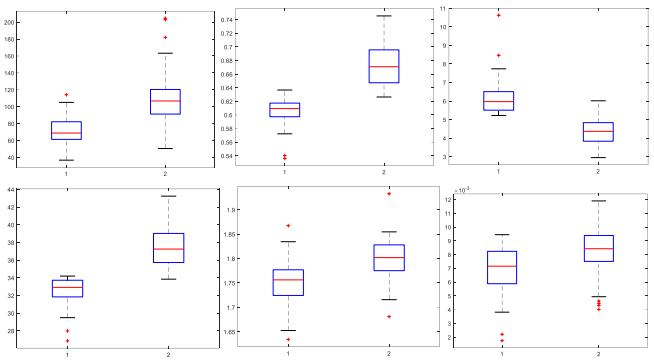

Fig. 6: Boxplots showing the evolution of features across two chronological classes of Seurat's paintings: (a) Mean of gradient magnitudes, (b) SRE, (c) LRE, (d) RP (e) HFD, and (f) Number of edges. Class 1 corresponds to the early period and Class 2 to the mature period of his work.

Fig. 6c and Fig. 6d shows the changes in LRE and RP. An increasing trend is also observed in HFD and in the number of edges, as seen in Fig. 6e and 6f. Overall, this map of changes in the features that co-shape the formation of the two data classes is consistent with the existence of two phases in Seurat's work, as established by art scholars. In the first phase (before mid-1880) more impressionistic style with looser brushstrokes, and in the second phase (after mid 1880) a disciplined pointillist style.

C. Signac

The same procedure was adopted in order to investigate the spontaneous grouping of Signac artworks in different time periods and to find the connection of the groups with specific features that contribute to their formation. The optimal number of clusters was determined equal to three. The composition of the formed clusters, based on the vector of extracted features, is presented in the heatmap of Fig. 7. We observe that the first cluster primarily consists of artworks from early years, that is true classes 1-12 corresponding to years 1882-1895. The second cluster comprises artworks created mainly in the artist's mid years that is true classes 5-26 (years 1886-1916). The third cluster mainly includes ground truth classes 27–37, associated with the years 1917–1935. The three clusters overlapping is expected, as explained in Seurat case.

The most informational features resulting from the feature ranking procedure are: SRE, HFD, HGRE and Entropy in the histogram of the hue channel.

In the following boxplot figures, class 1 corresponds to early year's period, class 2 to middle year's period and class 3 to late year's period. Looking at Fig. 8a for the classification ability of the SRE feature in terms of the three classes we can conclude that, Signac in his earliest, Impressionist-inspired works uses more elongated brushstrokes indicated by the intermediate SRE values, then in the following years Signac had established a repertoire with pointillism-style, dot wise, brushstrokes indicated by high SRE values and in last years he used more compact depictions and unified surfaces in his works indicated by low SRE values.

From the boxplot of Fig. 8b, we observe that 3rd class has lower values of HFD, interpreted to paintings with less texture and a shift to simplicity, while in 2nd class the higher values of HFD imply rich textures paintings with lots of fine detail.

In Fig. 8c appears the boxplot of HGRE feature. While there is no noticeable difference on average value of HGRE between classes 1 and 2, indicating similar tonality in the gray level in early and central period artworks, in class 3 we see a higher value of HGRE, indicating the presence of longer runs of high-intensity pixels that correspond to the regions with uniform high intensity that clearly dominate the watercolours of this period (Fig.2c). In Fig. 8d is shown the boxplot of the entropy in the histogram of the hue channel. We note from the figure lower hue entropy to the last period pointing to less complex artworks with a more harmonious colour scheme. In the central period the higher hue entropy leads to paintings of vibrant and complex visual appearance.

Some useful conclusions, regarding the artist's choices per time period, arise also from the observation of other features. In Fig. 8e and 8f we see the boxplots of mean saturation and mean value. Although there were no major changes across the three classes, a small variation is observed from lower saturation and higher brightness in the last period that imply paintings more soft, pastel, gentle, and calm compared to those of the first period which are characterized by (slightly) higher saturation and lower brightness referring to paintings more intense and passionate.

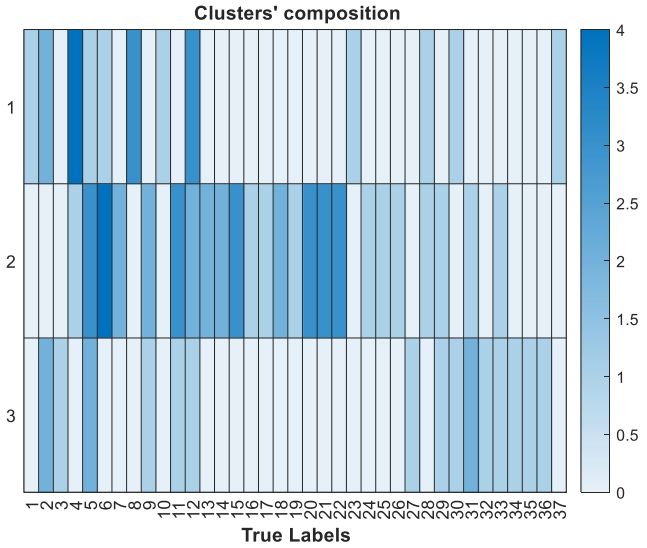

Fig. 7: Heatmap showing the composition of the three clusters formed from engineered features of Signac's paintings, in terms of their true chronological labels. The true labels correspond to the year of each painting's creation, ranging from 1 (1882) to 37 (1935).

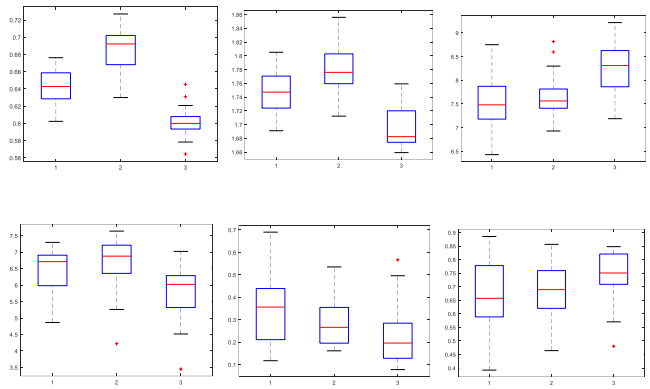

Fig. 8: Boxplots showing the evolution of two features across three chronological classes of Signac's paintings: (a) SRE, (b) HFD, (c) HGRE, (d) Entropy in Hue Histogram, (e) Mean Saturation, and (f) Mean Value. Class 1 corresponds to the early period, Class 2 to the middle period, and Class 3 to the late period of his work.

D. Comparison with artworks of Monet and Pissarro

This section describes an experiment aiming to explore the natural clustering of the different artistic periods of Seurat and Signac, in combination and in relation to artworks by Monet and Pissarro. Specifically, a new dataset is created, consisting of 10 paintings from Seurat's early period and 10 from his mature period, as well as 10 paintings from each of Signac's early, middle, and late periods. Additionally, 10 works by Monet and 10 watercolour paintings by Pissarro are included. All artworks were sourced from WikiArt. Claude Monet is recognized as a leading figure of Impressionism during the late 19th and early 20th centuries, while Camille Pissarro was active as both an Impressionist and later a Pointillist during the 19th century. In this experiment, only Pissarro's watercolour works were selected. These four artists were contemporaries, shared personal connections, and likely influenced each other's artistic development [18, 28].

This experiment is expected to confirm the correlation between the works of Signac's early period and the artworks of Seurat's early period with Monet's Impressionist works. It is also expected to reveal a correlation between the works of Signac's middle period and the works of Seurat's late period (Pointillism works). Finally, a correlation is expected between the watercolours of Pissarro and the paintings of the late period of Signac. For that reason, the number of clusters is set equal to three.

The heatmap in Fig. 9 shows the composition of the three clusters formed after the clustering procedure, using the same engineered features as in the previous experiments. The first cluster primarily groups artworks from Signac's middle period and Seurat's mature period, both characteristic of Pointillist technique. The second cluster mainly contains artworks from Signac's early period, Seurat's early period, and Monet's works, which are associated with the Impressionist technique. Finally, the third cluster predominantly includes Pissarro's watercolours and the late-period watercolours of Signac. As seen in the figure, the formed clusters reflect the influences and connections between the artists, as expected.

Fig. 9: Heatmap showing the composition of the three clusters formed from engineered features of Seurat, Signac, Pissarro and Monet paintings. The 1st cluster contains primarily paintings from the mature period of Signac and Seurat, the 2nd cluster paintings from early period of Signac, early period of Seurat and Monet paintings and finally the 3rd cluster contains all Pissarro paintings together with almost all Signac late period paintings

V. CONCLUSIONS AND FUTURE WORK

This study investigates the division of Pointillist painters Georges Seurat's and Paul Signac's artworks into chronological periods using unsupervised machine learning techniques. Clustering of engineered features extracted from artists' digitized paintings from WikiArt, revealed two periods in Seurat's career, corresponding to his early, Impressionist-influenced works and his later, mature Pointillism period. For Signac, three periods were shaped, reflecting his evolution from early exploratory works to disciplined Pointillism, followed by a more relaxed style in his later years. The most significant features forming these clusters include Run length features, Hausdorff fractal dimension, and edge statistics. Results from these experiments match fairly well against the reported in literature styles evolution in painters' oeuvre.

The present work is intended as a case study focusing on two Pointillist artists. To address this limitation, future work will extend the research to a wider set of artists and broaden the sources of digital artworks. Furthermore, a more in-depth analysis of the experimental results could also be conducted by examining the precise composition of the chronological groups of paintings and correlating them with specific phases of artist's lives, influences from other painters, travels, political and social events. Unsupervised machine learning techniques can also contribute to the broader field of digital cultural heritage preservation and representation [30].

Finally, methods for explaining machine learning model predictions, such as LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (Shapley Additive Explanations) [29], will also be employed to gain deeper insight into the chronological clustering of paintings using CNNs.

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