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Identifying influences between artists based on artwork faces and geographic proximity

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ABSTRACT

The investigation of influences in artists' works has been a subject of interest for art historians for many years. Therefore, computational methods can provide a new perspective for identifying these influences' relationships. Indeed, several studies in computer science have proposed techniques to analyze similarities between paintings using various features. Faces are a crucial aspect of perception in art and have also been the focus of several studies in computational aesthetics. In our previous work, we proposed a method for analyzing artworks and evaluating the influence of artists. The present study improves upon the previous research by extending the analysis of influences considering second-degree influences between artists and the impact of geographic proximity, obtaining better results in terms of Recall than the previous work. In addition, we evaluated the capability of our method to detect work-to-work relationships between each pair of artworks by the artists, and we found plausible and interesting results, even though they have not yet been proven in the literature. By conducting further analysis of data extracted from the faces of works of art, the goal is to enhance the previous findings in the literature and foster further discussion and collaboration between the fields of art and computer science. The objective is not to provide a definitive answer to the question of influences but to stimulate further research in this area, pointing out new possibilities of influence and explanations about these influences.

1. Introduction

Aesthetics is the branch of philosophy that studies concepts and theories of art and the aesthetic experience and is often referred to as the philosophy of art [1]. With the high-quality digitization of paintings in recent years, studying them through computational means has become possible [2]. The main themes explored by computational aesthetics are centered around solving problems such as artist identification and style prediction [3]. Other popular topics include retrieving similar paintings, painting dating, and forgery detection. A good example of the benefit of collaboration between computer science and art is the work by Rakhimol and Maheswari [4], where the authors propose an efficient technique for restoring damaged areas in paintings.

The ability to recognize others is a crucial human skill refined through evolution. People can recognize an average of 5000 different faces [5]. This is why faces are often the main focus of attention in paintings and other artworks, as observed in the study of eye movement by Yarbus [6] in 1965. In the field of art history, the analysis of similarities and differences in faces is a critical tool used to study paintings. Despite the extensive study of facial features in art, Schenk and Stumpel [7] noted that face comparison is rarely cited as a method. This may be due to the universal and everyday nature of facial recognition and memory, leading art historians to not consider it a specific aspect of their field.

Implementing algorithms and automatic evaluations for artworks has sparked debates due to a lack of understanding and skepticism about computers performing subjective tasks. According to Spratt and Elgammal [8], some of the responsibility for these concerns lies with computer scientists who tend to overgeneralize computer analysis capabilities instead of collaborating with art historians. Foka [9] emphasizes that art historians are not seeking systems that make interpretations automatically. Instead, the author suggests that computer science should focus on areas such as creating a painting recovery system, signature detection, and ethnicity recognition. Collaboration between these two fields is crucial for advancing the study of art.

Faced with this discussion and these questions, the present work extends the methodology already proposed in our previous work [10] to identify the influences among the artists. The aim is

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not to fully resolve the issue of influences through our methods but to provide new evidence of potential relationships between artists and identify the features in which these relationships can be observed, bringing some possible explanations. In this work, we carry out further investigations on data extracted from the faces of works of art to improve the results already found and possibly stimulate more discussions in the art and computer science research communities to further collaboration. Our main contributions are the extension of influence analysis by considering the second-degree influences between artists, i.e., artist X influences artist Y who influences artist Z, the impact of geographic proximity, and also the tests of our method in detecting work-to-work relationships between each pair of artists' works of art.

2. Related work

Influence in an artist's work is a topic that often sparks discussions among art historians because it is a complex matter and involves objective and subjective tasks [2]. According to Hermerén [11], there are basic conditions for art scholars to assess influence in the arts: temporal and contact conditions, which refers to the contact between the influenced artist and the influencer's work, change conditions, which says that some characteristic of the influenced artist's work has changed after the contact with the influencer's art, and similarity conditions, which refer to remarkably similar visual characteristics. Numerous work examine similarity conditions from a computational perspective. Shamir [12] compares the artistic styles of some painters. He used the WND-CHARM algorithm [13] [14], which uses numerical image content descriptors, to measure similarities between the artists' styles. The analysis showed that Pollock's style is more similar to Van Gogh's than to other painters' styles. In their next work with Tarakhovsky [15], they also utilized the WND-CHARM algorithm to analyze 994 paintings by 34 artists, calculating a matrix of similarities that can be visualized through a phylogeny [16], a tree-shaped diagram commonly used in biology to illustrate the relationship between species. Castellano et al. [17] proposed a method for visual link retrieval in paintings that uses a deep neural network model to learn visual attributes in an unsupervised way and similarities among paintings are obtained through unsupervised nearest neighbor search. Based on a qualitative evaluation, the author concluded that the method finds visual links that are justifiable by human perception. Wallraven et al. [18] suggest that even if less effective than humans, computer vision algorithms can provide clues about associating categories using low-level appearance information, as GIST, entropy, color features, among others. Saleh et al. [19] also tackled the issue of identifying influences among artists, using semantic visual features to create an influence suggestion system. The authors used a dataset of 1710 images of paintings by 66 artists, including 13 painting styles and 76 pairs of positive influences claimed by art historians as the ground truth. They calculated the similarity between the artists using high-level semantic features, including class feature vectors, GIST descriptors, and HOG descriptors. GIST descriptors are an image processing technique that extracts information about the spatial distribution of intensity frequencies in an image, while HOG (Histogram of Oriented Gradients) descriptors extract information about the orientation and distribution of intensity gradients. With this information, they determined the Hausdorff distance between the artists, treating each artist as a set of points comprised of their artworks. The results were evaluated using Recall, defined as the ratio of correct influences detected to the total known influences in the ground truth. The authors achieved a top-5 recall of 34.21% using GIST features. All these works explore the characteristics of the artwork in a global way.

Faces are a crucial aspect of the perception of art and have been the focus of numerous studies. According to Yarbus [6], people's eyes are immediately drawn to faces in a painting. In art, the ability to identify differences and similarities is a fundamental skill that art historians use to analyze paintings. Although facial features are often used in the analysis, face comparison is rarely cited as a method. According to Schenk and Stumpel [7], this is because recognizing faces is a universal and everyday skill, not necessarily considered specific to the field of art history. An experiment with 96 lay participants in art showed that laypeople categorize faces in the same way as art specialists, based on region or painting school [7]. The authors concluded that artists from the regions and schools involved in the tests used recognizable facial types and that art scholars could use this phenomenon to attribute works of art. There is a need for a multidisciplinary approach that combines theories of art history, perception, and computational facial recognition to study these issues further. Some studies have explored computer analysis of faces in paintings, including Sablatnig et al. [20] who proposed a method to analyze the authorship of mini portraits by evaluating the shape of faces and brush strokes. Gupta et al. [21] used a deep learning-based facial recognizer to verify the identity of Renaissance-era portrait models. Schmid et al. [22] developed an attractiveness metric based on various face measurements, including symmetry, Golden ratio metrics, and metrics used by Renaissance artists.

In our previous work [10], we propose a method to determine the influence between artists based on the portrayal of faces in their artwork. We evaluated four visual feature groups: Composition, Proportion, Position, and Expression. The best results were achieved with the composition feature group, which incorporates color and clutter features, with a Recall of 50.00% in a subset of the dataset based on a time frame. When the closest influences were computed using all features, the results were even better, with a Recall of 65.38% in this subset. In the present work, we re-evaluate the results by considering second-degree influences, which occur when one artist influences another artist through a third party. We calculated the results in terms of Recall for the complete dataset and for a subset based on a time frame, for each feature group and the feature combination. We also tested the impact of geographic proximity on the results by combining the distance measure with the geographic distance between the countries where each artist lived. The results were evaluated and compared based on Recall too. Finally, we evaluated the ability of our method to detect work-to-work relations by calculating the Euclidean distance between works of art by each pair of artists. The following section presents the dataset used in our study and the extracted visual features.

3. Dataset

In our previous work [10] we created a dataset of features extracted from artwork faces. The dataset is based on 66 artists identified in Saleh et al. [19]. After searching these artists on WikiArt,[2] we found 62 and scraped 17,904 images of their paintings. To evaluate influences based on facial features, we used OpenFace 2.0 software [23] to detect and crop the faces. Of the 62 artists found on Wikiart, 56 artists had faces detected in their works by OpenFace 2.0, totaling 8435 faces detected from 4437 paintings . Therefore, we kept only the largest face in paintings with multiple faces to avoid duplication. The final dataset includes 4437 faces from 56 artists. Fig. 1 illustrates such process to build the dataset.

We call the dataset with these 56 artists the *complete dataset*. In addition, to analyze a specific period in time, we created a

[2] https://www.wikiart.org/

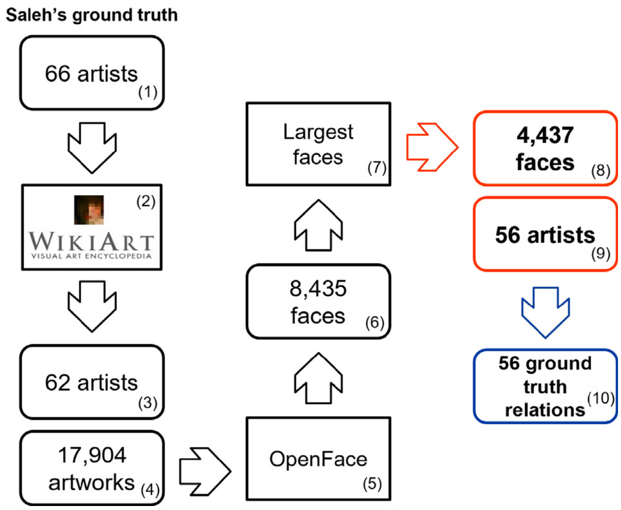

Fig. 1. Dataset and ground truth construction process. Initially, we identified the 66 artists indicated by the ground truth of Saleh's [19] work (1), we searched for them on Wikiart (2) where we found 62 artists (3). Of these 62 artists, we downloaded 17,904 artworks (4) and through the Openface software (5) we detected 8435 faces (6). Of the artworks with more than one face, we kept only the largest face (7), thus leaving 4437 faces (8) from 56 different artists (9). These artists have 56 different relationships of influence among themselves, thus forming the ground truth used in this work (10).

temporal subset by only considering artists who lived until 1900, totaling 27 artists. This subset was created because the 20th century saw significant changes in art and its style [24].

In addition to detecting and cropping faces, OpenFace provides face information, including Eye Gaze, Head Pose, Rigid Shape, and Intensity of Action Units, for our analysis. Eye Gaze has gaze direction vectors in 3D coordinates and gaze angles for both eyes. Head Pose has a vector of head location and rotation relative to the camera in 3D coordinates. Rigid Shape is used to parameterize the face with landmarks detection [23]. Intensity information of 17 Action Units and the presence of 18 other units are used to classify facial expressions based on Ekman and Friesen's [25] proposal.

The relationship between facial aesthetics and attractiveness is well established in the literature [26]. Schmid et al. [22] systematically investigated this relationship and found that specific measurements of a face can be used to assess its attractiveness. Using the calculation proposed by Schmid et al. and the landmarks extracted by OpenFace, we extracted Neoclassical canons, symmetry information and golden ratios. The Neoclassical canons are measures used by Renaissance artists to determine the beauty of a face based on landmarks and the coefficient of variation between pairs and trios of segments. Symmetry information includes 21 different symmetry measures between the left and right sides of the face, such as the ratio of distances, natural log of the ratio of distances, and adjusted distance difference. Golden ratios are 17 different ratios calculated between pairs of facial segments vertically and horizontally to approach the ideal ratio of 1.618. The closer the measurements are to 1.618, the more beautiful the face is.

Finally, using the cropped face images, we extract color, clutter, and proportion features. The color features include the mean and standard deviation of each of the three color channels in the HSV (Hue-Saturation-Value) space. The clutter feature, used to measure the degree of visual complexity in an image, was measured as the ratio of edge pixels to the total number of pixels in the image. The proportion features include differences between eye sizes, ratios of eye and face sizes, ratios of mouth and face sizes, and the ratio of face size to the entire painting size.

Therefore, we propose to explore the following feature groups in our dataset:

1. **Composition**: Color and clutter features;
2. **Proportion**: Proportion features, Neoclassical Canons, Symmetry, and Golden ratio;
3. **Position**: Features of gaze, pose, and rigid shape;
4. **Expression**: Features of the intensity of AUs and amount of active AUs.

In case of missing values, we input the feature median value of the artist's paintings. For further details, please refer to Dalmoro and collaborators' work [10].

3.1. Ground truth and evaluation metric

The ground truth used in our work was presented by Saleh et al. [19]. They presented in their paper the ground truth of influences, composed of 66 artists and 76 pairs of positive influences between them, claimed by art historians.

As discussed in Section 3 and detailed in Fig. 1, of the 66 artists that made up Saleh's ground truth, we kept only the 56 artists who had some face detected in their works. Based on the 56 artists present in our dataset, the ground truth is composed of 56 influence relationships between pairs of these artists, thus being a sparse dataset, where most artists have a number of influencers smaller than five or even there is none. As in the previous work [10], to make comparisons with competitive works, we propose to identify how many of the influence relationships calculated by our method are in accordance with the ground truth, which represents the true influence relationships. Therefore, the metric used in the evaluation of the work is Recall, as defined below:

$$Recall = \frac{h}{N}, \tag{1}$$

where h is the number of ground truth influence relationships found among the computed influence relationships, and N is the total amount of ground truth influence relationships.

In the next section, we detail the proposed methodology.

4. Methodology

In our previous work [10], we identified influence relationships between artists based on their faces. To identify possible relationships between artists, we proposed to measure the similarity among the faces painted by artists based on the extracted features, as described in Section 3. Our method calculates the similarity between faces using the asymmetric distance based on the Hausdorff distance defined by:

$$D_{q\%}(P^i, P^j) = \overset{q\%}{\underset{k}{\max}}\, d(p_k^i, P^j), \tag{2}$$

where we consider the distance $D_{q\%}(P^i, P^j)$ between influenced artist i and artist influencer j as the Euclidean distance q percentile between each painted face $p_k^i \in P^i$ of artist i for the set P^j of painted faces of artist j. The Euclidean distance between the two artworks is defined by:

$$d(p_k^i, p_l^j) = \sqrt{\sum_{s=1}^{n} (p_{ks}^i - p_{ls}^j)^2}, \tag{3}$$

where $p_l^j \in P^j$ is the face of the artwork by artist j, and s is a feature of the set of extracted features that represented each face. We used $q = 50\%$, which represents the median distance between the face p_k^i and the set P^j. For more details, see our previous work [10].

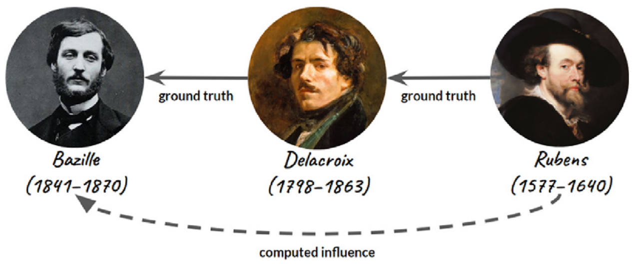

Fig. 2. In this case, the ground truth presents Peter Paul Rubens as an influencer on Eugene Delacroix, and Eugene Delacroix as an influencer on Frederic Bazille, while in our computed relations, Peter Paul Rubens appears as an influencer on Frederic Bazille. When considering the second-degree influences, we assume the method correctly identified this indirect relationship.

After calculating the distance between each artist and their possible influencers, we generate a list of the top-5 closest artists in terms of distance $D_{q\%}$, for each of the artists in the dataset and compare it to the ground truth. The following sections present the main contributions of the methodology in addition to the influences computed using the feature groups.

4.1. Second-degree influences

In the present work, we propose a new way to evaluate the influence relationships that we call *second-degree influences*. We consider second-degree influences when the methodology suggests that a certain artist j influenced artist i, but the j artist influenced an m artist who ultimately influenced the i artist. We hypothesize that, once it is not reported in the ground truth, certain painters' characteristics may have passed through generations, and our methodology may help to identify these possible influences.

Fig. 2 provides an example of second-degree influences. In this case, if our method finds that Rubens influenced Bazille, we consider it correct if Rubens influenced Delacroix, who influenced Bazille.

For the Recall calculation, we consider the same ground truth defined in Section 3.1, but we also considered second-degree influences on both the numerator and the denominator. Thus, the definition of the Recall calculation to evaluate second-degree influences is given by the equation:

$$Recall = \frac{h + h_{2nd}}{N + N_{2nd}} \tag{4}$$

where h and N are the same terms defined in Eq. (1), N_{2nd} is the number of second-degree relations present in the ground truth and h_{2nd} is the number of second-degree relations of N_{2nd} that our method indicated. We compute results for the complete dataset, for the temporal subset, and for each feature group and feature combination.

4.2. Geographic proximity

In addition to second-degree influences, we want to test how much we can improve our results considering the *geographic proximity* between the artists. In such a case, we hypothesize that artists have a greater chance of influencing others in a close space in the world. After calculating the $D_{q\%}$ (Eq. (2)) that computes the similarity measure between each pair of artists, we calculate the geographic distance between the countries where each artist lived and then combine the $D_{q\%}$ similarity measure with the geographic distance.

To define geographic distance, we calculated the Euclidean distance of the countries where each artist lived based on latitude and longitude. We then normalized the computed distance values to the interval [0; 1], whereby a value closer to 0 indicates that countries are closer, and a value closer to 1 suggests they are more distant. Indeed, we do not classify as close or far since the normalized distance is used as weights, combined with the similarity measure as follows:

$$D_w = (D_{q\%} \cdot (1 - w)) + (D_{q\%} \cdot w \cdot D_g), \tag{5}$$

where $D_{q\%}$ is a similarity measure described in Eq. (2), D_g is the calculated geographic distance between countries and w is the proportion of the $D_{q\%}$ value that will be weighted by D_g. The idea is that the closer the artists are in the space, the similarity measure $D_{q\%}$ is reduced, therefore considering them more similar, i.e., the closer they are geographic, the lower should be the $D_{q\%}$ value. For w, we tested and compared the values of 0.2, 0.5 and 0.8, where 0.2 weights 20% of the $D_{q\%}$ value, 0.5 weights 50% of the value and 0.8 weights 80%. The evaluation and comparison between the results are based on the calculation of *Recall*.

4.3. Work-to-work relationships

Finally, we want to understand whether the information extracted from the faces of artworks can detect work-to-work relations in addition to artist-to-artist similarity. Twenty influence relationships found with our methodology, without considering second-degree and geographic influences, were in accordance with the ground truth. For each pair of artists present in those relationships, we calculated the Euclidean distance between each pair of artworks for each feature group, through Eq. (3). For each work of each influenced artist, we selected the three works of the influencer artist who have the lowest Euclidean distance of all the feature groups. We took care that the works of art by the influencing artist were created before the work of the influenced artist. As there is no ground truth with which we can evaluate our similarity results work by work, we bring some of the results found. As there are no theoretical foundations for some of the pieces of art evaluated, we present some of the results we studied and indications of their plausibility.

5. Results

Our study aims to analyze the influence relationships among artists by examining the faces in their artworks. To achieve this, we compare each painted face of an artist with each painted face of another artist, for every pair of artists in our dataset. While avoiding the assessment of impossible influence relationships, such as cases where an influencer artist was born after the death of the influenced artist, we were able to evaluate 2072 distinct influence relationships using our complete dataset and 610 using the temporal subset. These relationships include all influence relationships present in the ground truth.

After comparing all painted faces for each of the possible influence relationships, our method found the five closest artists for each of the 56 artists using the $D_{q\%}$ distance (Eq. (2)) for each feature group (composition, proportion, position, and expression), as described in Section 4. Each feature group generated 278 different influence relationships for the complete dataset and 138 influences for the temporal subset. The results were evaluated by doing a feature combination. To do this, we selected the half of relationships with the smallest distance $D_{q\%}$ from the 278 relationships in the complete dataset and 138 relationships in the temporal subset of each feature group, resulting in 139 relationships for the complete dataset and 69 relationships for the temporal subset for each group. The selected relationships were then merged and duplicates were removed, resulting in different numbers of relationships for each feature combination.

Table 1
Recall values obtained considering second-degree influences for each dataset. The best results are highlighted in bold.

Feature group	Complete dataset	Temporal subset
Composition	29.85%	53.85%
Proportion	25.37%	50.00%
Position	26.87%	42.31%
Expression	29.85%	50.00%
Feature Combination	**49.25%**	**82.14%**
Our previous work [10]	32.14%	65.38%
Saleh et al.[19]	38.81%	46.42%

Table 2
Recall values for the *complete dataset* resulting of combining the similarity measure $D_{q\%}$ from our previous work [10] with the geographic distance D_g for each value of w. The best results are highlighted in bold.

Feature Group	$w = 0.2$	$w = 0.5$	$w = 0.8$
Composition	25.00%	21.43%	21.43%
Proportion	23.22%	23.22%	28.57%
Position	25.00%	26.79%	37.50%
Expression	25.00%	26.79%	35.71%
Feature Combination	**37.50%**	**41.07%**	**39.29%**

Table 3
Recall values for the *temporal subset* resulting of combining the similarity measure $D_{q\%}$ from our previous work [10] with the geographic distance D_g for each value of w. The best results are highlighted in bold.

Feature Group	$w = 0.2$	$w = 0.5$	$w = 0.8$
Composition	50.00%	42.31%	42.31%
Proportion	38.46%	42.31%	46.15%
Position	34.61%	34.61%	38.46%
Expression	34.61%	38.46%	38.46%
Feature Combination	**65.38%**	**61.54%**	**50.00%**

Table 4
Recall values for the *complete dataset* resulting of combining the similarity measure $D_{q\%}$ *considering second-degree influences* with the geographic distance D_g for each value of w. The best results are highlighted in bold.

Feature Group	$w = 0.2$	$w = 0.5$	$w = 0.8$
Composition	37.50%	16.81%	17.70%
Proportion	37.50%	39.29%	46.43%
Position	35.71%	35.71%	46.43%
Expression	**41.07%**	**41.07%**	**51.79%**
Feature Combination	30.09%	32.74%	30.97%

Table 5
Recall values for the *temporal subset* resulting of combining the similarity measure $D_{q\%}$ *considering second-degree influences* with the geographic distance D_g for each value of w. The best results are highlighted in bold.

Feature Group	$w = 0.2$	$w = 0.5$	$w = 0.8$
Composition	57.69%	27.66%	27.66%
Proportion	**61.54%**	**69.23%**	**73.08%**
Position	46.15%	46.15%	50.00%
Expression	46.15%	50.00%	53.85%
Feature Combination	48.94%	48.94%	42.55%

We evaluated these results for second-degree influences and geographical proximity for the complete dataset and temporal subset, both for each feature individually and for their combination. Our evaluations were based on the Recall metric, as described in Section 3.1.

Regarding the second-degree influences, for the complete dataset, we reached a result of $Recall = 49.25\%$ with the feature combination (410 influence relationships). For the temporal subset, the result obtained was $Recall = 82.14\%$ (181 influence relationships). Our previous work reached $Recall = 32.14\%$ for the complete dataset and $Recall = 65.38\%$ for the temporal subset. To compare the results, we recalculated Saleh's work [19] considering second-degree influences and only the 56 artists used in our methodology. The result obtained for the complete dataset is $Recall = 38.81\%$ (290 influence relationships), and $Recall = 46.42\%$ for the temporal subset (124 influence relationships). All such results of the feature combination presented can be consulted in Table 1, together with the comparison with the work by Saleh et al. [19] and our previous work [10]. It is easy to note that the second-degree analysis improved our results, with a 17.11% increase in Recall for the complete dataset and 16.72% for the temporal subset. Our results were 10.44% higher than Saleh's, for the complete dataset and 35.72% for the temporal subset, in terms of Recall.

Regarding the geographical proximity, we used the distance between artists computed by our methodology described in Section 4 and combined them with the Euclidean distance between the artists' countries, calculated using latitude and longitude. We tested three levels of weighting, $w = 0.2$, $w = 0.5$, and $w = 0.8$. Firstly, without considering second-degree influences, the results improved as the weighting value increased for the feature groups of proportion, position, and expression, as can be seen in and compared the results in Table 2 (complete dataset) and Table 3 (temporal subset). However, the composition feature group results were better when considering a smaller value to weight the geographical proximity metric. So, the best results were obtained when the weighting value was $w = 0.5$ for the complete dataset, with $Recall = 41.07\%$ (403 influence relationships) and $w = 0.2$ for the temporal subset with $Recall = 65.35\%$ (181 influence relationships).

When we consider second-degree influences together with geographical proximity, the behavior of feature groups with respect to weights is similar to when we do not consider second-degree influences, i.e., the composition feature group is the only one of the four feature groups that reduce the Recall value when increasing the level of weighting according to Table 4 (complete dataset) and Table 5 (temporal subset). In addition, using geographic proximity and second-degree influences, the feature combination does not present a better result than feature groups individually. Even comparing with the results without considering second-degree relations, the individual results of all features in both datasets are superior, except for the results of the composition feature group for $w = 0.5$ and $w = 0.8$ and the results of the feature combination in all weights. With the complete dataset, the feature group with the best result is Expression, with $Recall = 51.79\%$ with $w = 0.8$. In contrast, the feature combination has its best result at $w = 0.5$ with $Recall = 32.74\%$ (403 influence relationships). With the temporal subset, the feature group with the best result is the Proportion with $Recall = 73.08\%$ with $w = 0.8$. In comparison, the feature combination has its best result at $w = 0.2$ and $w = 0.5$ with $Recall = 48.94\%$ in both (181 and 180 influence relationships respectively).

Note that to calculate the influence relations weighted by geographic proximity, it is necessary to have the calculated numerical value of the distance between the artists. In his work, Saleh provided only the influence relations calculated by his method without the numerical values of the distances. This is enough for us to recalculate his results regarding Recall, which considers the correct relationships indicated, but does not allow us to recalculate his results regarding geographic proximity.

To understand how far our results deviate from chance, we calculated what the results would look like if we generated them randomly. To do this, we used the binomial distribution [27]. The binomial distribution, in Eq. (6), is a discrete probability distribution that models the number of successes in a sequence of independent and identical experiments.

$$P(x) = \frac{n!}{(n-x)!x!} p^x (1-p)^{n-x}, \tag{6}$$

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where the parameters n is the number of trials, and p is the probability of success in each trial. In our work, the number of trials is the number of influence relationships generated in our results, and the probability of success is the number of correct relationships among the possible influence relationships between artists. If the results were generated randomly, the recall for the complete dataset would be on average 13.46%, and for the temporal subset, it would be 22.62%. Using the binomial distribution, we also calculated the probability of the result being generated by chance for each of our best results. The probability of our results being generated by chance for all tested results was less than 1%. This shows that our results were not given by chance and that our method is a good way to identify the influence between artists.

In the same sense, to assess how much geographic proximity may be biasing our results when combined with features, we calculated our result using only geographic proximity. Of the 2072 possible influence relationships of the complete dataset, 282 are artists from the same country, thus having the geographic distance value $D_g = 0$. Of these artists, 17 are in the ground truth. So our result using just geographic proximity would be Recall $= 30.35\%$. Of the 610 possible relationships for the temporal subset, 158 are from artists from the same country, and nine are in the ground truth, obtaining Recall $= 33.33\%$. The results in Table 2 indicate that for the complete dataset, without considering second-degree influences, the obtained results considering only the geographic distance perform better. In this case, the combination of geographic proximity does not help our previous method to improve the Recall values. On the other hand, as presented in Tables 3–5, we obtained better results when we consider second-degree influences.

5.1. Work-to-work analysis

Finally, we investigate if the information extracted from faces in artworks can reveal relationships of influence work-to-work. For this, we calculated the Euclidean distance between each artwork by the influenced and influencing artists, considering each group of features. We use only the 20 influence relationships identified in our work, without considering second-degree or geographic influences, and confirmed as true, according to the ground truth. In this way, we calculated the distance between 291,198 artworks. To understand which artworks by the influencing artist may have had the greatest influence on the artworks by the influenced artist, for each artwork by the influenced artist we kept only the three artworks by the influencing artist that had the least distance, considering all groups of influencers features. That is, we considered the smallest distance between the calculated distances based on each group of features and then we kept the three works with the smallest of these distances. So, in the end, we kept 9488 pairs of artworks.

Most pairs of artworks were selected using our method based on the composition (3955 pairs) and position (1.849 pairs) feature groups, while the proportion and expression groups had fewer next pairs (365 pairs and 319 pairs, respectively). In Table 6 we can see the pairs of artworks with the smallest Euclidean distance calculated for each feature group among the 9488 pairs selected. In three of the four groups of features, the closest pair of artwork are from the influential relationship between Pierre-Auguste Renoir and Edouard Manet. For example, the artworks “Portrait of a lady with a black fichu” by Edouard Manet (left) and “Woman with a white jabot” by Pierre-Auguste Renoir (right), illustrated in Fig. 3, represent the closest faces regarding the composition feature group and have light colors, low contrasts, and less marked shapes. This indicates that our method is coherent considering that Renoir and Manet were important French painters of the 19th century and were part of the impressionist movement: *“The Impressionists used looser brushwork and lighter colors than previous artists. They abandoned traditional three-dimensional perspective and rejected the clarity of form that had previously distinguished the more important elements of a picture from the lesser ones”.*.[3] Please, note that these two artists are present in the ground truth dataset we are using.

Fig. 3. “Portrait of a lady with a black fichu” by Edouard Manet (left) and “Woman with a white jabot” by Pierre-Auguste Renoir (right).

Of the 9488 pairs of artworks studied, for each relationship of influence, we identified which work by the influencing artist was most indicated by our method as the closest to the artworks of the influenced artist (most influential artwork). If more than one artwork was indicated the same number of times, we selected the artwork with the shortest distance between the artworks of the influenced artist. To make a work-to-work comparison, we looked for the artwork of the influenced artist that was closest to the most influential artwork of the influencing artist.

In Table 7, we can observe which artworks are considered most influential by our method in each of the influence relationships and which work of the influencing artist is indicated as closest.[4]

We highlight some qualitative aspects of the artworks found as most similar according to our method.[5]

- The work “Girl in a hat with her arms crossed” by Pablo Picasso was closer to the work “Not Detected” by David Hockney. The two faces have the same orientation, looking to the right, with neutral expressions and more reddish tones (Fig. 4). The feature that best explains the similarity here is the *position* feature group.
- The work “Angel Fernandez de Soto and his Friend” by Pablo Picasso was closer to the work “Jurisprudence (final state)” by Gustav Klimt. The two faces were portrayed in shades of gray, with more serious expressions (Fig. 5). The feature that explains the computed similarity is the *composition* feature group.
- The work “Rosalie Reisener” by Berthe Morisot was closer to work “Young woman with a pink shoe (Portrait of Berthe Morisot)” by Edouard Manet. Both faces have less detail and shadows, with similar skin tones and faces orientation facing slightly to the right. Coincidentally, Manet’s work is a portrait of Berthe Morisot (Fig. 6). Again, the feature that explains the best similarity here is the *composition* feature group.

[3] https://www.theartstory.org/movement/impressionism/

[4] Link to the images of artworks in the table: https://brpucrs-my.sharepoint.com/:x:/g/personal/bruna_dalmoro_edu_pucrs_br/EbZhI58_h3FAgo0TXad2Y-gBNCy5EdaJvWYl2r-UI5Fv_Q?rtime=A85Et5IZ20g

[5] In some cases, we showed only the cropped faces from the artworks to focus on the details.

Table 6
Pairs of artworks that present the smallest Euclidean distance for each feature group, where *Influential artwork* is from the *Influencer artist* and *Pair artwork* is from *Artist*.

Artist	Influencer artist	Influential artwork	Pair artwork	Feature group
Pierre-Auguste Renoir	Edouard Manet	Portrait of a lady with a black fichu	Woman with a white jabot	Composition
Peter Paul Rubens	Titian	Crowning with Thorns	Adoration of the Magi	Proportion
Pierre-Auguste Renoir	Edouard Manet	Madame Brunet	Serving Girl from Duval's Restaurant	Position
Pierre-Auguste Renoir	Edouard Manet	Madame Brunet	Berthe Morisot and Her Daughter Julie Manet	Expression

Table 7
Influence relationships analyzed work-to-work (the artist and his/her influencer), the influencer artist's most influential artwork, and the influenced artist's principal pair artwork. We use the pairs of analyzed artists (influencers and influenced) correctly indicated by our work and present in the ground truth.

Artist	Influencer artist	Most influential artwork	Principal pair
Frederic Bazille	Pierre-Auguste Renoir	Romaine Lascaux	Portrait of Édouard Blau
Giovanni Bellini	Andrea Mantegna	St. Euphemia	Madonna with Trees
William Blake	Raphael	St. John the Baptist in the Desert	The Angel of Revelation
Francis Bacon	Pablo Picasso	Armchair 'California'	Study for a portrait of John Edwards
Francis Bacon	Rembrandt	Three female heads with one sleeping	Study for the Nurse in the film 'Battleship Potemkin'
Marc Chagall	Pablo Picasso	Portrait of a tailor Soler	Noah's Cloak
Eugene Delacroix	Michelangelo	Sistine Chapel Ceiling: The Delphic Sibyl	Jewish Bride
Eugene Delacroix	Peter Paul Rubens	Deborah Kip, Wife of Sir Balthasar Gerbier, and Her Children	Arab Fantasia
Théodore Géricault	Michelangelo	Sistine Chapel Ceiling: The Delphic Sibyl	Portrait of young boy, probably Olivier Bro
David Hockney	Pablo Picasso	Girl in a hat with her arms crossed	Not Detected
Gustav Klimt	Pablo Picasso	Angel Fernandez de Soto and his Friend	Jurisprudence (final state)
Edouard Manet	Berthe Morisot	Rosalie Reisener	Young woman with a pink shoe (Portrait of Berthe Morisot)
Franz Marc	Vincent van Gogh	Woman in the 'Cafe Tambourin'	Fabulous Beast II
Piet Mondrian	Vincent van Gogh	The Baby Marcelle Roulin	Portrait of a Girl with Flowers
Berthe Morisot	Edouard Manet	Marguerite de Conflans Wearing Hood	At the Ball
Pierre-Auguste Renoir	Edouard Manet	Madame Brunet	Serving Girl from Duval's Restaurant
Peter Paul Rubens	Michelangelo	Adam and Eve	Portrait of George Villiers, 1st Duke of Buckingham
Peter Paul Rubens	Titian	Madonna and Child with Sts Catherine and Dominic and a Donor	The Holy Family with St. Elizabeth
Titian	Giovanni Bellini	Madonna with Child	Portrait of Doge Marcantonio Trevisani
Diego Velazquez	Titian	Portrait of Count Antonio Porcia	Portrait of Pope Innocent X

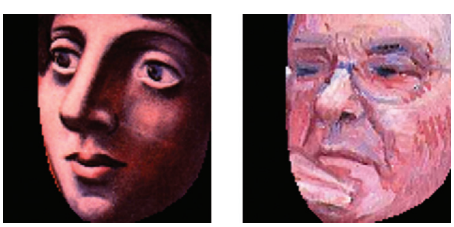

Fig. 4. Faces extracted from "Girl in a hat with her arms crossed" by Pablo Picasso (left) and "Not Detected" by David Hockney (right).

- The work "Marguerite de Conflans Wearing Hood" by Edouard Manet was closer to work "At the Ball" by Berthe Morisot. The two works have white-skinned faces, dark hair and eyes, and look in similar directions with a neutral expression (Fig. 7). Once again, the *composition* feature group explains the found similarity.
- The work "Madame Brunet" by Edouard Manet was closer to the work "Serving Girl from Duval's Restaurant" by Pierre-Auguste Renoir. Skin tone and mouth shape are slightly different, but face orientation, gaze direction, eyebrows and eye colors are very similar (Fig. 8). The feature that best explains the similarity here is the *position* feature group.

Fig. 5. Faces extracted from "Angel Fernandez de Soto and his Friend" by Pablo Picasso (left) and "Jurisprudence (final state)" by Gustav Klimt (right).

Fig. 6. Faces extracted from "Rosalie Reisener" by Berthe Morisot (left) and "Young woman with a pink shoe (Portrait of Berthe Morisot)" by Edouard Manet (right).

Fig. 7. Faces extracted from "Marguerite de Conflans Wearing Hood" by Edouard Manet (left) and "At the Ball" by Berthe Morisot (right).

Fig. 8. Faces extracted from "Madame Brunet" by Edouard Manet (left) and "Serving Girl from Duval's Restaurant" by Pierre-Auguste Renoir (right).

Fig. 9. "Marguerite de Conflans Wearing Hood" by Edouard Manet (left) and "At the Ball" by Berthe Morisot (right).

Fig. 10. "Madonna and Child with Sts Catherine and Dominic and a Donor" by Titian (left) and "The Holy Family with St. Elizabeth" by Peter Paul Rubens (right). The analyzed faces are highlighted with the yellow square.

Fig. 11. "St. John the Baptist in the Desert" by Raphael (left) and "The Angel of Revelation" by Willian Blake (right).

Fig. 12. "Portrait of Count Antonio Porcia" by Titian (left) and "Portrait of Pope Innocent X" by Diogo Velasquez (right).

The distances between the works of art are calculated considering only the faces portrayed in the artworks. However, surprisingly some artworks have similarities as a whole. The two works in Fig. 9, "Marguerite de Conflans Wearing Hood" by Edouard Manet and "At the Ball" by Berthe Morisot, portray white women with dark hair and eyes wearing white dresses. In the "Madonna and Child with Sts Catherine and Dominic and a Donor" by Titian and "The Holy Family with St. Elizabeth" by Peter Paul Rubens, in Fig. 10, the faces present different directions and expressions. Both faces of characters that interact with other characters in a dynamic and very expressive way. Both works in Fig. 11, "St. John the Baptist in the Desert" by Raphael and "The Angel of Revelation" by Willian Blake, in addition to having similar facial shapes, expressions, and gaze directions, depict standing naked men, wrapped in cloth, with their right arm extended to the sky. Titian's "Portrait of Count Antonio Porcia" and Diogo Velasquez's "Portrait of Pope Innocent X", in Fig. 12, portray a bearded white man looking at the observer. In addition, they are positioned with their bodies facing the left with the left arm supported.

In all these analyzed artworks we can observe a probable level of coincidence regarding the mentioned aspects of the paintings that are not specifically on the faces. Here we hypothesize that in addition to the similarity between the faces, there is a general similarity in the composition of the paint. This may indicate that when analyzing the faces through their position, size, gaze, facial expression, color, and shadow, we can study the general context of the paint. Of course, we need to consider that we are evaluating works within the context of the style of artists who have influenced each other, so there should likely be a certain standard in the way of painting portraits that is permeated from one artist to another. Anyway, this aspect is not in the scope of this paper, and it needs more precise and qualitative individual analysis, as made in the four examples of Figs. 9, 10, 11 and 12.

6. Final considerations

This research analyzed the relationships between 56 artists based on their art features and geographical location. The top-5 closest relationships for each artist were evaluated using a distance measure for each proposed feature group: composition, proportion, position, and expression. The study also looked at the effect of second-degree influences and geographical proximity, for both the complete dataset and the temporal subset. The Recall metric was used to assess the results, which were compared to Saleh et al.'s work [19] (also recalculated considering second-degree influences). Saleh's work showed a Recall of 38.81% for the complete dataset and 46.42% for the temporal subset. Our previous results [10] showed a Recall of 32.14% for the complete dataset and 65.38% for the temporal subset when combining features. Using the methodology of the second-degree influence proposed in this paper, i.e., the Recall increased to 49.25% for the complete dataset and 82.14% for the temporal subset.

According to Table 1, feature groups that obtained the best performance were Composition for both the complete dataset (Recall = 29.85%) and for the temporal subset (Recall = 53.85%), and Expression for the complete dataset (Recall = 29.85%). The Composition feature group comprises color and clutter information, a measure of visual complexity, while the Expression feature group identifies the presence and intensity of the AUs, that is, whether or not the portrayed face has a more or less intense facial expression. According to our method, these are good characteristics for comparing artworks by different artists in search of influence relationships. We believe that the temporal subset in these cases presents better results, mainly because we kept only artists who preceded the 20th century, which was when there was a significant change in style in the arts, with the disappearance of dominant styles in artists, giving way to stylistic versatility [24]. An artist with greater variability of styles in his artworks can cause our method to generate relationships of similar distance with several artists without any of them being more prominent, making it difficult to find the correct relationship.

To gauge the impact of geographical proximity, the results were combined with the Euclidean distance between the artists' countries and tested with different weighting values. The results improved as the weighting values increased for the proportion, position, and expression feature groups. However, the best results for the composition feature group, without considering second-degree influences, were obtained with a weighting value of $p = 0.2$. The overall best results were achieved with a weighting value of $p = 0.5$ for the complete dataset, resulting in a Recall of 41.07% and a weighting value of $p = 0.2$ for the temporal subset Recall = 65.38%. We can see that second-degree influence provides better results than only with geographic information. When we consider geographic proximity and second-degree influences at the same time, our feature combination results do not improve the results of feature combination of previous works, but when we individually evaluate the group of Expression features for the complete dataset we obtain the best result of the work, with Recall of 51.79%, with $p = 0.8$ weighting. For the temporal subset, the Proportion feature group resulted in a Recall of 73.08%, with $p = 0.8$. The second-degree influences approach brings a good gain in the results, including Saleh's results, indicating that there may be characteristics of an artist's work that pass through "generations of influence". Geographical proximity improves the results of our previous work [10], especially when we look at the complete dataset without making a temporal subset.

We also analyzed the result of the method comparing work to work, showing which works of art possibly had the greatest influence on the artist's artwork. In our analysis, we identified some pairs of works of art that are similar regarding facial characteristics. Surprisingly, some artworks were also similar in the general composition of the painting. This may suggest that facial characteristics may indirectly indicate the general context of the artwork. In future work, it is possible to further investigate the patterns of specific facial features in the overall style and composition of artworks. For example, the current study focused on the influence of faces on artists' relationships. Still, future research could explore how individual facial features behave within specific artistic styles or movements and use these findings to further hone the search for relationships of influence through the faces.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.cag.2023.05.028.

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