2022 35th SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI) | 978-1-6654-5385-1/22/$31.00 ©2022 IEEE | DOI: 10.1109/SIBGRAPI55357.2022.9991755

Measuring the influence of painters through artwork facial features

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***Abstract*—Computational aesthetics is a subfield of computer vision that seeks to understand the human aesthetic perception of images and image sequences. The main objective is to create systems that allow different aesthetic decisions, trying to approximate the judgment of a human being about the images. In this work, we explore the problem of identifying influence among artists based on visual features detected in their artworks. In particular, we are interested in investigating the similarity of faces in paintings to design the artists' influence. In our methodology, we propose four groups of features to characterize the faces, and we show that the similarity of faces to finding artists' influence, shows promising results when compared to the recently proposed methods.**

I. Introduction

At its origin, studies of aesthetics within philosophy had art as one of the central objects of their questioning [1]. In recent years, as paintings are digitized in high quality, it has become possible to study paintings computationally [2]. The main themes widely explored by computational aesthetics are mainly related to solving issues such as artist identification and style prediction. Therefore, other problems such as retrieval of similar paintings, painting dating, and detection of forgery are also very popular [3]. However, the application of algorithms and large-scale automatic evaluations of works of art has generated discussions. Not only the development and application of these new technologies are mostly unknown by art scholars, but there is much concern about their implementation. As analyzed by Spratt and Elgammal [4], a good part of the concerns of art history researchers is precisely due to the lack of knowledge and disbelief in how computers could perform such subjective tasks performed by specialists. According to the authors, part of the responsibility for these concerns is how computer scientists disseminate their work, generalizing the power of computer analysis to global and complex problems rather than seeking to collaborate with art historians to solve specific problems in the field.

Foka [5] emphasizes that art historians are not looking for systems that make interpretations automatically, as recent new methods have gone beyond analyzing the content of the images of artworks. Furthermore, Foka listed topics that deserve greater attention in computer science for facilitating the work of art historians, such as creating a painting recovery system, signature detection, and ethnicity recognition, among others, and reinforces the importance of approach between these two areas in collaborative work. Thus, the work of Foka [5] and Sprat and Elgammal [4] converge in the thought that computational advances applied in art history have to be questioned not because they threaten to replace art historians in their tasks, but on the contrary, because they may not have a practical utility as the computer scientists may expect.

Keeping this discussion and questions in mind, we explore the problem of identifying influence among artists in the present work. In particular, we are interested in investigating the similarity of faces painting in order to design the possible influences. It is also necessary to emphasize that we do not intend to solve the question of influences through our methods, even because it is not a closed subject in literature. Instead, we intend to provide evidence of possible relationships between artists and identify in which characteristics these relationships can be noticed to be input for specialists investigating these relationships. In our methodology, we propose four groups of image features to characterize the faces, and we show that the similarity of faces, for the purpose of finding artists' influence, shows promising results when compared to the recently proposed methods.

II. Related Work

Defining whether another influenced one painter's work is a question that is often difficult to resolve and generates discussions among art historians. From a computational point of view, these influence relationships can be identified through the similarity between the artists' works of art, with the aid of visual features. Shamir and Tarakhovsky [6] used the WND-CHARM scheme, commonly used for biomedical image analysis, to extract 4027 features from 994 paintings by 34 artists and calculated a matrix of similarities that can be visualized through a phylogeny, tree-shaped diagram commonly used in biology to visualize the relationship between species [7]. Saleh et al. [8] also addressed the issue of identifying influence among artists using visual features extracted from their artworks. The authors' idea was to create an influence suggestion system using semantic visual features, inspired by style classification work. The authors used a dataset of 1,710 images of paintings by 66 artists containing 13 painting styles. To assess the results, they collected 76 pairs of positive influences claimed by art historians to compose the

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ground truth. To calculate the similarity between the artists, the authors used high-level semantic features extracting the class feature vector, GIST descriptors, and HOG descriptors, and calculated the Hausdorff distance between the artists, treating each artist as a set of points composed of her/his artworks. The evaluation of the results is done by calculating the Recall, which is defined as the ratio between the number of correct influences detected and the total of known influences on the ground truth. Saleh et al. [8] best result was top-5 recall 34.21% using GIST features. Another work [9] also proposes a model with a similar goal, but using VGG [10] with visual features, not focused on faces, as in this work.

An important human skill is to recognize faces. Throughout evolution, we have honed our abilities to process unknown and familiar faces. In a recent study, researchers estimated that people know about 5,000 different faces on average [11]. As a result, faces catching our attention. For those looking at a painting, for example, faces are the main points of attention when present. In an important study by Yarbus [12] on eye movement, in 1965, it was possible to notice that the fixations of the observers' eyes were particularly directed to the faces of the individuals in the painted scene already in the first moments of the observations. In art, the perception of differences and similarities is a fundamental skill through which art historians analyze paintings. According to Schenk and Stumpel [13], although faces in painting have been studied from many angles and art historians use facial features in their analysis, they rarely cite face comparison as a method. For Schenk and Stumpel, art historians do not reflect on the fact that they apply facial recognition and memory skills, perhaps because recognizing faces is a universal and everyday skill to be considered specific in the field of the study of art history. In an experiment with 96 lay participants in art, results showed that laypeople categorize faces in the same way as art specialists, regarding their region or painting school [13]. The authors concluded that artists from the regions and schools involved in the tests used and reused recognizable facial types and that art scholars could make use of this phenomenon to make attribution of works of art. Furthermore, the authors stress that there is a need to study issues like this using a multidisciplinary approach, combining theories of art history, perception, and computational facial recognition.

Some works have already explored computer analysis of faces in paintings. Sablatnig et al. [14] propose a method to analyze the authorship of mini portraits of the Austrian royal family by evaluating the shape of faces and brush strokes. Gupta et al. [15] used a deep learning-based facial recognizer to verify the identity of renaissance-era portrait models, seeking to find which different paintings portrayed the same person.

Our work meets the analysis of influence between artists, assuming that the representation of faces is an important part of the artworks, where the authors use inspiration and dedicate much work. Seeking to collaborate with insights both for the history of art and for research in computational aesthetics, we seek to point out in what kind of characteristics these faces are most similar, taking into account the Composition of the painting, the proportions used in the construction of the faces, their position and the presence and intensity of facial expressions. In the next section, we present the dataset used in the present work and the extracted visual features.

III. Dataset and Features

We build our dataset based on the ground truth presented by Saleh et al. [8], briefly described in Section II. Firstly, as Saleh and collaborators did not make their dataset publicly available, we must create our dataset from scratch. Fortunately, they presented the ground truth of influences in their paper, composed of 66 artists. We searched the 66 artists on the WikiArt website and found 62 of them. Through scraping, we downloaded 17,904 images of paintings from the 62 artists found. Since the objective of this work is to evaluate the influence based on the faces of the artworks, we firstly detected and cropped the faces using the OpenFace 2.0 software [16]. We chose this software to perform this task as it provides other information related to the cropped face that is useful for analysis, e.g., landmarks, pose, and gaze, detailed later. In this process, 8,435 faces were detected in 4,437 works of art performed by 56 artists (presented in Table I). All faces are cropped, aligned vertically from nose to center, and a mask is applied to remove the background from the image. An example of face detection and cropping is shown in Figure 1. Some artworks have more than one face detected, in these cases, we consider only the largest face of each painting so that a work is not represented more than once in the dataset. Therefore, the final dataset, which we call the *complete dataset*, comprises 4,437 faces from 56 artists. Note that the difference between Saleh's (66) and our work (56) is due to some artists we discarded because artworks do not have faces.

Furthermore, we tested to compute the relationships only for a certain period. As the 20 century went through transformations in the paradigm of how art itself and style are seen within art [17], we made a cut based on the period of life of the artists, which we call the *temporal subset*. In this dataset, we kept all the artists who lived until 1900, i.e., 27 artists, identified with '*' in Table I.

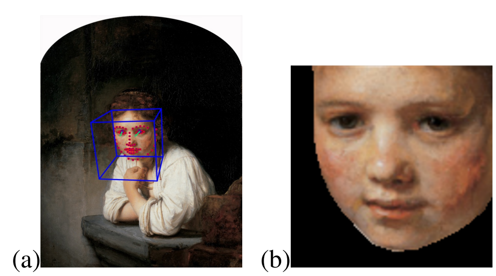

Fig. 1. *Girl at a Window*, (Rembrandt, 1645). In (a) the detected face is shown with landmarks (red), gaze (green) and head orientation (blue). In (b) the cropped face of (a) with the mask after removing the background.

In addition to detecting and cropping faces, OpenFace provides a series of face information, which we use in our work.

https://www.wikiart.org/

Firstly, the Eye Gaze concerns two gaze direction vectors in 3D coordinates, one for the left eye and one for the right eye, and the horizontal and vertical angle of gaze direction for both eyes; secondly, the Head Pose, i.e., a vector of the location of the head relative to the camera in millimeters, and vector of the rotation in radians, in eD coordinates with the camera being the origin, around the X, Y, Z axes; thirdly, the Rigid shape used to parameterize the face using a set of parameters, used in the landmark detection process, where the rigid shape parameters describe the position of the face in the image (scaling, rotation and translation) [16]; andand finally, the Intensity information (0 to 5) of 17 Action Units (AUs) and presence (0 absent, 1 present) of 18 other AUs, used as a way to classify human facial expression, as proposed by Ekman and Friesen [18].

The aesthetic perception of faces is related to attractiveness. According to Graf and Landwehr [19], the literature on aesthetic preferences treats aesthetic taste and attractiveness judgments as equivalent concepts. Thus, measuring the attractiveness of a face is also measuring its aesthetics. In their work, Schmid et al. [20] systematically investigated the relationship between specific measurements of a face and its attractiveness. Using the calculation proposed by Schmid et al., applied to landmarks extracted by OpenFace, we extracted the following information:

A) Neoclassical canons: Measures proposed by artists from the Renaissance period as guides for drawing beautiful faces define 9 pairs or trios of face segments that, according to them, should have equal sizes. Based on landmarks, 6 of the Neoclassical Canons were calculated, and the measure used was the coefficient of variation between these pairs and trios of segments, where the closer to zero, the closer they would be to the ideal measure.

B) Symmetry: Three different measures of symmetry between the left and right sides, based on the centerline of the face, for the top of the eyebrows, inner edge, outer edge and base of the eyes, width of the nose, top and side of the lips, and width of the face, totaling 21 measures. The measurements are the ratio of the distances, the natural log of the ratio of the distances, and the adjusted distance difference. For the fitted difference and natural log of the ratio, a value of zero implies symmetry, and the farther from zero, the more asymmetric.

C) Golden ratios: Measure 17 different ratios between the size of pairs of face segments, vertically and horizontally, such as mid-eye distance to interocular distance, nose width to lip height, mouth width to nose width, etc. The original idea of the work that proposed these measures was to identify whether those values approached the golden ratio, i.e., 1.618. The closer the measurements are to 1.618, the more beautiful the face would be.

Finally, using the images of the cropped faces, we extract color and clutter information and use the landmarks, and other proportion features in addition to the ones used to study the attractiveness: *i)* Colors: Mean and standard deviation of each of the three color channels in the HSV space; *ii)* Clutter: Ratio of edge pixels compared to the number of pixels in the image; and *iii)* Proportions: Difference between eye sizes, the ratio of eye size to face size, the ratio of the center of mouth size to full mouth size, the ratio of mouth size to face size, and the ratio of face size compared to the size of the entire painting.

So, we propose to explore the following feature groups, as listed in Table II: *i)* **Composition**: Color and clutter features; *ii)* **Proportion**: Proportion features, Neoclassical

TABLE I
ARTISTS THAT MAKE UP OUR FINAL TEMPORAL DATASET. ARTISTS WITH '*' ON THEIR DEATH DAY REPRESENT ARTISTS WHO LIVED UNTIL THE 19TH CENTURY AND ARE CONSIDERED IN THE TEMPORAL SUBSET.

Artist	Birth Day	Death Day	Detected Faces
Albrecht Durer	1471-05-21	1528-04-06*	302
Alfred Sisley	1839-10-30	1899-01-29*	4
Andrea Mantegna	1431-01-01	1506-09-13*	390
Andy Warhol	06/08/1928	22/02/1987	125
August Macke	1887-01-03	26/09/1914	25
Auguste Rodin	1840-11-12	17/11/1917	28
Berthe Morisot	1841-01-14	1895-03-02*	91
Camille Pissarro	1830-07-10	13/11/1903	53
Caravaggio	1571-09-29	1610-07-18*	118
David Hockney	09/07/1937		71
Diego Velazquez	1599-06-06	1660-08-06*	147
Edouard Manet	1832-01-23	1883-04-30*	122
Edvard Munch	1863-12-12	23/01/1944	64
El Greco	1541-01-01	1614-04-07*	192
Ernst Ludwig Kirchner	1880-05-06	15/06/1938	61
Eugene Delacroix	1798-04-26	1863-08-13*	100
Francis Bacon	28/10/1909	28/04/1992	57
Francisco Goya	1746-03-30	1828-04-16*	244
Franz Marc	1880-02-08	04/03/1916	2
Frederic Bazille	1841-12-06	1870-10-28*	34
Frida Kahlo	06/07/1907	13/07/1954	108
Georgia O'Keeffe	1887-11-15	06/03/1986	1
Gerhard Richter	09/02/1932		9
Giovanni Bellini	1430-01-01	1516-11-29*	137
Gustav Klimt	1862-07-14	06/02/1918	62
Gustave Caillebotte	1848-08-19	1894-02-21*	49
Henri Rousseau	1844-05-21	02/09/1910	57
Jan van Eyck	1395-01-01	1441-07-09*	106
Jasper Johns	15/05/1930		3
Jean Auguste D. Ingres	1780-08-29	1867-01-14*	262
Johannes Vermeer	1632-10-31	1675-12-15*	43
Juan Gris	1887-03-23	11/05/1927	3
Kazimir Malevich	1879-02-23	15/05/1935	33
Leonardo da Vinci	1452-04-15	1519-05-02*	52
Lorenzo Ghiberti	1378-01-01	1455-12-01*	2
Marc Chagall	1887-07-07	28/03/1985	1287
Max Beckmann	1884-02-12	28/12/1950	52
Michelangelo	1475-03-06	1564-02-18*	175
Norman Rockwell	1894-02-03	08/11/1978	281
Pablo Picasso	1881-10-25	08/04/1973	185
Paul Cezanne	1839-01-19	22/10/1906	124
Paul Klee	1879-12-18	29/06/1940	4
Peter Paul Rubens	1577-06-28	1640-05-30*	696
Pierre-Auguste Renoir	1841-02-25	03/12/1919	736
Piet Mondrian	1872-03-07	01/02/1944	6
Raphael	1483-01-01	1520-01-01*	344
Rembrandt	1606-07-15	1669-10-04*	438
Robert Campin	1375-01-01	1444-04-26	73
Robert Motherwell	24/01/1915	16/07/1991	1
Roy Lichtenstein	27/10/1923	29/09/1997	4
Sandro Botticelli	1445-01-01	1510-05-17*	205
Théodore Géricault	1791-09-26	1824-01-26*	41
Titian	1488-01-01	1576-08-27*	425
Vincent van Gogh	1853-03-30	1890-07-29*	152
Wassily Kandinsky	1866-12-16	13/12/1944	7
William Blake	1757-11-28	1827-08-12*	42

Canons, Symmetry, and Golden ratio; *iii)* **Position**: Features of gaze, pose, and rigid shape; *iv)* **Expression**: Features of the intensity of AUs and amount of active AUs.

In the case of images (faces) where some features cannot be extracted, we input the missing values with the median of the feature of the artist's paintings. For visual features extracted with world coordinates, the values were normalized, according to $z_i = \frac{x_i - \mu}{\sigma}$, where μ is the mean and σ is the standard deviation of all observations of the feature, x_i is the original value of observation i of the feature, and z_i is the normalized value of observation i. In the next section, we detail the proposed methodology.

IV. Methodology

To identify possible relationships between artists, we propose to measure the similarity among the faces present in the works of art. For an artist j to have been influenced by an artist i, artist i must have been born before the artist j, or at least have been contemporaries. To ensure that the influence relationships follow this logic, we only consider relationships in which the artist influencer i was born before the death of the influenced artist j. As each artist has painted pieces-of-art (each one with a face already analysed in our dataset), to calculate the influence between two artists we consider each artist as a set composed of the faces of his/her artworks, where artist i has the set of faces P^i and artist j has the set of faces P^j. From there, we calculated the similarity between faces using the asymmetric distance $D_{q\%}$ based on the Hausdorff distance proposed in [8] and defined by:

$$D_{q\%}(P^i, P^j) = \max_k^{q\%} d(p_k^i, P^j), \tag{1}$$

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. We used $q = 50\%$, which represents the median distance between the face p_k^i and the set P^j, for comparison purposes with the results of the work by Saleh et al. [8].

A. Evaluation

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. As previously discussed, the ground truth we used, provided by Saleh et al. [8], was constructed only with consensual influence relationships among art historians. 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 less than 5 or even there is none. As this is a sparse dataset, compared to our list of top-5 computed influence relationships, metrics such as accuracy is not the best assessment option. A good evaluation metric, which even allows us to compare with Saleh's work, is to identify how many of the influence relationships calculated by our method are in accordance with the ground truth, representing the true influence relationships. Therefore, the metric used in the evaluation of this work is Recall, defined as $Recall = \frac{|h|}{N}$, where $|h|$ is the number of ground truth influence relationships found among the top-5 computed influence relationships, and N is the total amount of ground truth influence relationships. As detailed in Section III, we created four different groups of visual features: Composition, Proportion, Position, and Expression. Using each group separately, we generated the top 5 influence relationships for each artist, based on Equation 1, and ratings in terms of Recall. We also evaluate the results by combining the result of feature groups, which we call the *feature combination*. For this, from the set of top-5 influences computed by each feature group, we selected only the influence relationships that had the smallest distance $D_{q\%}$ between the artists, based on the median, i.e., we kept only half of the influence relationships with the smallest distance of each feature group. We then combined influences from all groups, excluding repeated influence relationships, and then evaluated the results in terms of Recall.

TABLE II
RESULT OF CALCULATIONS USING EACH GROUP OF VISUAL FEATURES SEPARATELY AND COMPARISON WITH THE RESULTS OF SALEH ET AL. [8] FOR 56 ARTISTS. THE BEST VALUES ARE HIGHLIGHTED IN BOLD.

Feature group	Complete dataset	Temporal subset	Features Combination: Complete dataset	Features Combination: Temporal subset
Composition	25.00%	**50.00%**		
Proportion	21.43%	38.46%		
Position	23.21%	30.77%	32.14%	**65.38%**
Expression	21.43%	34.61%		
Saleh et al. [8]	**37.50%**	46.15%	**37.50%**	46.15%

V. Results

To compare the results fairly, we recalculated the results of Saleh et al. [8], using the same artists we have in our dataset, i.e., 56 artists and not 66. It comprised 290 influences considering the complete dataset and 124 influences for the temporal subset. The results for the complete dataset obtained Recall = 37.50%, based on 290 influence relations. For the temporal subset, the recalculation of results of Saleh's work reaches a Recall = 46.15%, based on 124 influence relations. The results can be seen in Table II. Using our methodology, we calculate the $D_{q\%}$ distance between the 56 artists considering each feature group separately, and then compute the top-5 influence relationships for each artist. Each feature group generated 278 different influence relationships for the complete dataset and 138 influences for the temporal subset, which were evaluated regarding Recall. After computing the results for each feature group separately, we performed the feature combination. We kept 139 of the 278 influence relationships for the complete dataset for each feature group. Removing the repeated relationships, we kept a total of 410 influence relationships, reaching **Recall = 32.14%**. As for the temporal subset, we kept 69 of the 138 influence relationships of each feature group, and, removing the repeated relationships, we kept a total of 181 influence relationships, reaching **Recall = 65.38%**. All such results of the feature combination presented can be consulted in Table II, together with the comparison with the work by Saleh et al. [8]. In addition, we also tested our method with only artists who have more than 10 detected faces (see Table I) resulting in 45 artists. Indeed, the numbers improved for the completed dataset, i.e., from 32.14% to 36.96%, in our method, and from 37.50% to 39.13% with Saleh's method. It is interesting to note that the original result of Saleh's work was Recall = 29%. By keeping in the ground truth only the relations of artists that painted faces, their results improved approximately by 9%, reaching Recall = 37.50% in our complete dataset. This indicates that our initial hypothesis that faces are important clues to identify influences between artists makes sense. In addition, the feature group that obtained the best results was the Composition group, which contains color and clutter information. Our results were even superior to the result of Saleh's work compared to the temporal subset.

A. Visualization

To facilitate the exploration of our results and obtain insights, we proposed an interactive web application , built in Shiny [21], where it is possible to visualize the influence relations obtained with our method in arc diagrams, as illustrated in Figure 2. In these diagrams, the artists are temporally ordered (from left to right), and when our methodology indicates some influence between them, they are connected by an arc, indicating that the older artist may have influenced the more recent artist. Furthermore, according to our method, the size of each artist's node represents how many other artists he/she has influenced. It is also possible to see in the diagram the influence relationships computed by our work that are in accordance with the ground truth (orange arcs), and which from our results that are not in the ground truth but were also identified by the work of Saleh et al. [8] (magenta arcs). Grey arcs show the 410 relations our method suggests, from the 2793 possible ones concerning the temporal order, while Saleh et al. [8] suggest 290 relations. In addition, Saleh and our method suggest 79 relations in common, and nine of them are consensus in the ground truth, while we suggest 20 and Saleh 21 correct relations if compared with the ground truth.

According to the ground truth, the artists who most influenced other artists are listed in Table III, while highlighted with '*' the artists our method also suggests in the top-10. One specific case to show the artist's influence and its reasons, as could be discussed with art experts, is the case of influencer Michelangelo. He influences Théodore Géricault, according to the ground truth and also according to our methodology. Such influence was explained using All Features Combination and the Composition feature group (Colors and clutter). Although we can not confirm that influence without a deep evaluation by art scholars and researchers, it seems reasonably to assume:"*Michelangelo was particularly important in Géricault's use of brisk, energetic brushstrokes and contrasting light effects created atmospheric scenes which broke free from the refined Néoclassical style of painting.*" .

TABLE III
ACCORDING TO THE GROUND TRUTH, LIST OF THE TOP-10 ARTIST INFLUENCERS AND THE NUMBER OF ARTISTS INFLUENCED BY THEM. WE HIGHLIGHTED WITH '*' THE ARTISTS OUR METHOD ALSO FIND IN TOP-10 INFLUENCERS.

Artist influencer	Number of influenced artists
Michelangelo*	6
Pablo Picasso*	5
Edouard Manet	4
Titian*	3
Vincent van Gogh	3
Paul Cezanne	3
Giovanni Bellini*	2
El Greco*	2
Peter Paul Rubens*	2
Diego Velazquez*	2

VI. Final Considerations

In this paper, we propose a method to assess the influence relationships between artists based on how they paint faces in their artworks. In addition, our proposal fits the art scholars' requirement by presenting reasons for the obtained relationships. We use four different groups of visual features: Composition, Proportion, Position, and Expression. Regardless of the test performed (complete dataset or temporal subset), the group that obtained the best results was Composition, which includes color and clutter features, reaching a Recall = 50.00% in the temporal subset. When evaluating the results by combining the closest influences computed from all features, we obtained even better results, reaching Recall = 65.38% in the temporal subset. Our results surpassed Saleh's results, except for the result obtained with the complete dataset, which may be explained by the fact that there were many transformations in art style in the 20 century [17], which may affect too much the painted faces. Interestingly, the results of Saleh et al. [8] also improved in the temporal subset and when only considering works of art containing faces. Indeed, it reinforces the hypothesis that faces are elements that inspire influence among artists and that help to identify those relationships.

Finally, this work has some limitations, firstly the method only works for painters who produced artworks with faces. Secondly, although we can say that found influence relations that confirm the groundtruth are correct, we can not say that the remaining ones are not plausible. Indeed, find out such relations are a complex research which should be executed by experts on the domain. As future work, we intend to investigate the influence relations taking into account also the place the artists live, as well as other possible analysis, such as the individually evolution of each artist along the time that can maybe influenced by various artists.

https://brunamdalmoro.shinyapps.io/influence_face_of_art/

https://www.theartstory.org/artist/gericault-theodore/

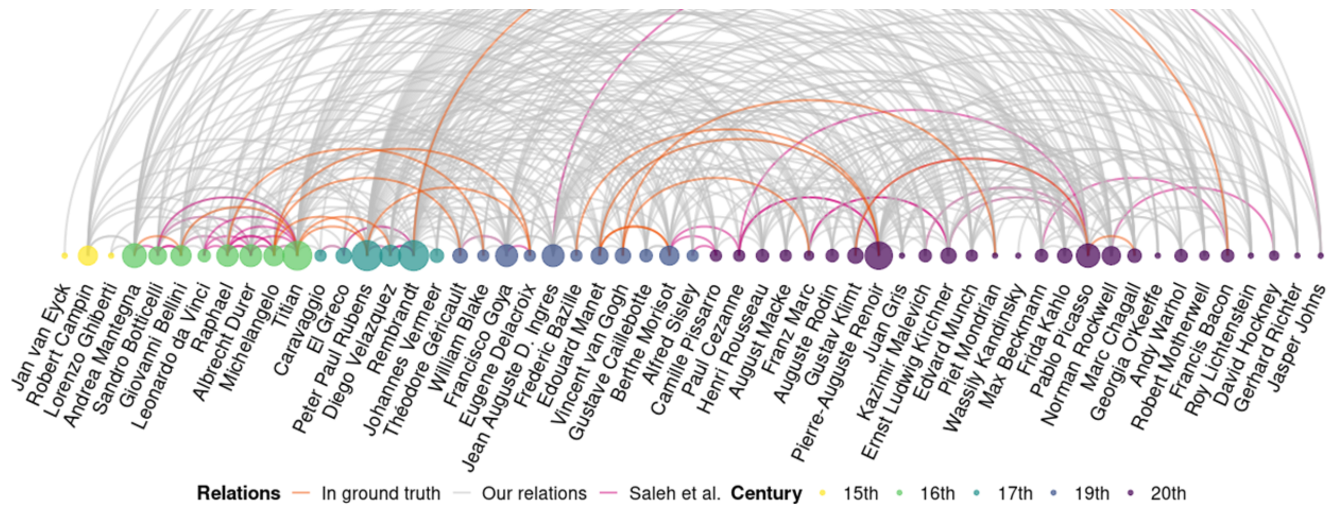

Fig. 2. Arc diagram of the 410 influence relationships computed by our work using the complete dataset and features combination. According to our methodology, the larger the nodes, the more influential the artist was. The highlighted arcs refer to relationships that our methodology suggested and that are also in the ground truth (in orange) and if they were also computed by Saleh et al. [8] (in magenta). In gray are the relationships that our method found but were not in the groundtruth.

ACKNOWLEDGMENT

The authors would like to thank to SIBGRAPI reviewers, and to the Brazilian agencies CNPq and CAPES.

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