Quantitative Modeling of Artist Styles in Renaissance Face Portraiture

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ABSTRACT

Renaissance portraits were depictions of some important royals of those times. Analysis of faces in these portraits can provide valuable dynastical information in addition to enriching personal details of the depicted sitter. Such studies can offer insights to the art-history community in understanding and linking personal histories. In particular, face recognition technologies can be useful for identifying subjects when there is ambiguity. However, portraits are subject to several complexities such as aesthetic sensibilities of the artist or social standing of the sitter. Thus, for robust automated face recognition, it becomes important to model the characteristics of the artist. In this paper, we focus on modeling the styles of artists by considering case studies involving Renaissance art-works. After a careful examination of artistic trends, we arrive at relevant features for analysis. From a set of instances known to match/not match, we learn distributions of match and non-match scores which we collectively refer to as the portrait feature space (PFS). Thereafter, using statistical permutation tests we learn which of the chosen features were emphasized in various works involving (a) same artist depicting same sitter, (b) same sitter but by different artists and (c) same artist but depicting different sitters. Finally, we show that the knowledge of these specific choices can provide valuable information regarding the sitter and/or artist. [1]

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Theory

Keywords

Face Portraiture, Feature Selection, Style Modeling

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1. INTRODUCTION

Portraiture has received a great amount of attention in recent years for varied reasons. Portraits encompass a wide range of art works such as sculptures, death masks, coins, pottery, tapestry, mosaics or even the modern day bank notes. The importance of portraiture has been vividly described in [17], where it is mentioned, "Because of the many different forms they take, portraits have been and can be used for a variety of dynastic, commemorative, judicial, personal, and propagandist purposes. They can be considered aesthetic objects, but they can equally be seen to act as a substitute for the individual they represent, or as conveying an aura of power, beauty, youth, or other abstract qualities". Figure 1 is a sample representation of various forms of portraiture.

Figure 1: Illustrations of different forms of portriature. Clockwise from top left: Mosaic, tapestry, pottery, painting, sculpture and banknote respectively.

Thus, portraits do not just depict likeness, but also engage with ideas of identity as they are perceived, represented, understood in different places and times. Face has arguably been one of the most salient aspects in all forms of portraiture. Most ancient and medieval era portraiture were depictions of people important in their own worlds–from kings and queens to other prominent aristocrats in the society.

Analysis of faces in portraits can offer significant insights into the personality, social standing, profession, age and gender of the subject they represent. However, this is not a simple task since a portrait can be "subject to social and artistic conventions that construct the sitter as a type of their time" [17]. Art historians are interested in understanding the styles of artists which, in turn, could aid in linking names or personal histories. In this context, face recognition technologies can be very valuable in providing a quantifiable source of analysis to art historians in interpreting such tasks.

Consider for instance, Figure 2, where Jan Van Eyck (left) and Rogier van der Weyden (right) painted portraits of the same individual, Nicolas Rolin. As noted in [17], Van Eyck's Rolin has a dignity of expression and a serious demeanour that is lacking in the frail and sadder image of Van der Weyden's Rolin. This could be due to the variations in the age of the sitter or may have been inspired by the purpose for which the portraits were made. Irrespective of the reasons, it is apparent that there are differences in works of the same sitter by different artists.

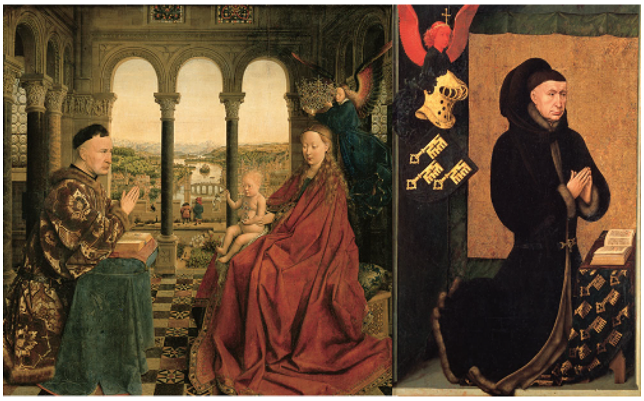

Figure 2: Example of artwork depicting same sitter by different artists.

Facial analysis and recognition tasks need to quantify such subjective (and sometimes abstract) distinctions of art connoisseurs into a concrete evaluation scheme whereby it is possible to understand characteristics of the sitter or a particular artist. In fact, modeling characteristics of the artist becomes an essential step in developing robust face recognition systems for portraits. We start by enumerating the challenges.

1.1 Challenges

Artist style modeling, facial recognition and analysis in artworks come with some noteworthy challenges apart from the typical ones such as variations in pose, illumination and facial expression. The important ones are listed below.

1. **Choice of features:** The chosen feature set should best justify artists' renditions and possess high discriminating power. Although there has been some preliminary work on this for paintings in general [10], there is little to no work on understanding how to model the style in face paintings or sculptures. Given these constraints, it is unlikely that any one feature set will be sufficiently accurate across all the example images. The chosen set may vary from artist to artist or sitter to sitter or both.

2. **Lack of sufficient training data:** Many existing feature selection methods rely on the availability of a significant amount of training data. This is rarely the case in our problem domain where we might be asked to identify the similarity between two faces drawn by different artists without the luxury of having more examples across different poses or ages of subjects. This can be attributed to the following reasons :
   (a) Difficulty in acquisition of such images from musuems across the world owing to their limited availability and cost.
   (b) Lack of a significant body of images, the authencity of which is well established. Merely pulling images from unofficial sites or basing research on the word of someone with either vested interests or without critical awareness would lack scientific integrity.
   (c) We need to logically choose a set of related images directed towards a particular demonstrative end and adhering to a particular period style. This, coupled with the fact that several such ancient art works have been dilapidated with time, has made their availability sparse.

3. **Variability in artists' styles:** As elaborated earlier, although portraits convey the likeness of an individual, they are subject to imagination of the artist. They can also reflect conventions or art pratices that are prevalent in the artist's cultural and social backgrounds. Due to this subjective interpretation of the artist, portraits of the same sitter can vary from artist to artist. This results in considerable variability in the renditions, which has to be accounted for by the face recognition/analysis algorithms.

1.2 Contributions

The following are the main contributions of the work.
1. Based on domain knowledge of artists' renderings, we identify the relevant feature set for the problem at hand; these being local features (LF) and anthropometric distances (AD).
2. Using statistical pattern recognition tools, we learn distributions of match and non-match scores, which we collectively refer to as the portrait feature space (PFS). We also validate the learned PFS with a subset of known match/non-match pairs. This is done over a dataset spanning over 50 image pairs by several artists.
3. We model artistic styles considering different combinations of sitters and artists, and identify features that are invariant across multiple works of a sitter or an artist. Further, we also analyze the relation between similarity scores in these various combinations.

1.3 Related Work

Facial analysis can be categorized under the broad heading of biometric identification [9]. A comprehensive survey of still and video based face recognition research is provided in [19]. These approaches can be broadly classified into three categories, namely holistic methods such as [14], feature based structural matching methods like [18], or hybrid methods like [1] depending on the representation in feature space. The choice of a particular method is largely governed by the application. The overwhelming majority of the face recognition techniques have been employed in surveillance, entertainment and law enforcement applications.

Analysis of paintings using sophisticated computer vision tools has gained popularity in recent years [13]. Computers

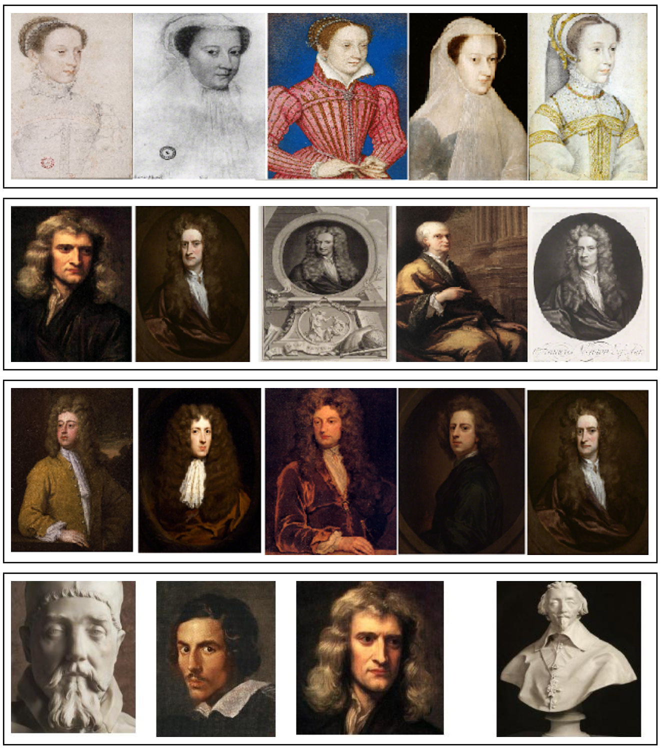

Figure 3: Example representation of the dataset. The top row depicts 5 works of artist Clouet portraying Mary Queen of Scotts (corresponding to scenario 1 described in text), second row from top represents 5 works depicting Newton by 3 different artists (Scenario 2) , Row 3 shows 5 sitters portrayed by Kneller (Scenario 3) and the bottom most row denotes works of different artists depicting different sitters (Scenario 4).

can extract features that are sometimes hard to discern by the human eye and thereby provide new insights that could enhance a connoissier's opinion. A recent work has explored application of computer based facial image analysis in artworks [15]. The proposed approach uses a statistical method for 3D face shape estimation to qualitatively evaluate the similarity [2].

While [15] focussed on validating one subject against 4 candidates, the problem we consider is broader. This work aims to model styles of artists and thereby learn features which are charcteristic of a sitter or an artist. In particular, we analyze various combinations of artists and sitters by considering a number of case studies involving portraits of diverse nature.

2. DESCRIPTION OF THE DATASET

We first provide an account of the dataset under consideration. We were provided over 50 pairs of images where the identities of the subjects were known beyond a doubt. These image pairs consisted of works of several artists such as Buggiano, Bandini, Holbein, Raphael among others. A sample representation of these known instances is shown in Figure 3.

In order to analyze various combinations of sitters and artists, we divide the data into different scenarios as follows.

1. Works of same sitter by same artist: Here we considered 2 cases namely;
   a) 5 works of artist Clouet depicting Mary Queen of Scotts;
   b) 5 works of artist Algardi depicting Innocent X.

2. Works of same sitter by different artists:Here we considered 3 cases namely;
   a) 8 works depicting Mary Queen of Scotts by 3 different artists;
   b) 5 works depicting Newton by 3 artists.
   c) 5 works depicting Dudley by 5 artists.

3. Works of same artist depicting different sitters:Here we considered 4 artists namely;
   a) 8 Works of artist Bernini depicting 4 different sitters;
   b) 5 works of Kneller depicting 4 different sitters, two of which happened to be Kneller himself;
   c) 20 works of artist Holbein depicting multiple sitters;
   d) 20 works of Van Miervelt depicting multiple sitters;

4. Works of different artists depicting different sitters:For this case, we combined all the above set of artworks to have works across sitters and artists.

3. LEARNING PORTRAIT FEATURE SPACE

We first review common pratices among the artists of the Renaissance era to understand relevant features. Subequently, we look at the feature set that would be applicable, given artistic trends. We then learn PFS on a subset of known instances and validate it on the remaining subset of known instances. An illustration of the procedure for learning the PFS is provided in Figure 4, the details of which are described in Secs 3.2, 3.3, 3.4 and 3.5.

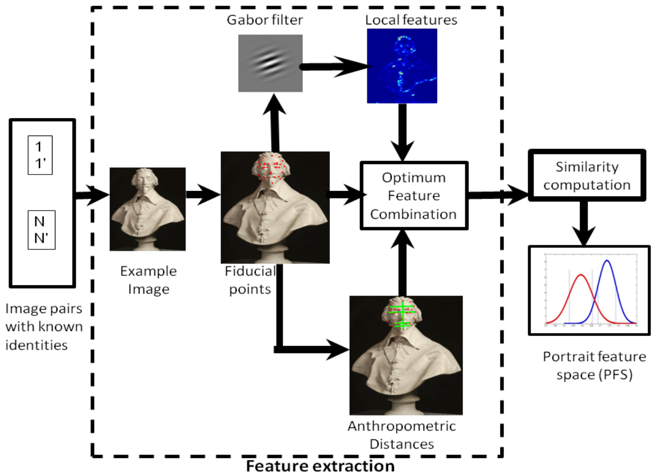

Figure 4: Learning the PFS— From the pair of images with known identities (1 through N), we compute local feature similarity and anthropometric distance similarity. These are then fused to obtain a single similarity score. The set of all such scores determine the match distribution (blue). Similarly, from the set of images which are known not to match, we obtain the non match score distribution (shown in red). (Please note that these distributions correspond to various artists and sitters).

3.1 Understanding Artists' Conventions

A detailed description of artists' drawing style in general (and not necessarily limited to facial profile) is provided in [11]. It is evident from [11] that while drawing a human body, lot of emphasis was laid upon maintaining the proportions of various parts.

More evidence regarding the importance of preserving certain salient body proportions (also known as anthropometric distances) in art works can be obtained from [16]. The importance of anthropometric distances is evident in various cultures starting from the ancient Egyptian era to the more recent Renaissance era. Leonardo Da Vinci extensively reported on the proportions according to which bodies and faces should ideally be depicted, and he applied these canons in his art [16]. Figure 5 illustrates the same. A historical appraisal of facial anthropometry from antiquity upto Renaissance has been provided in [6] to compare artists' concept of human profile. Further, prominent facial features specific to a person, were retained in art works of the same individual by different artists.

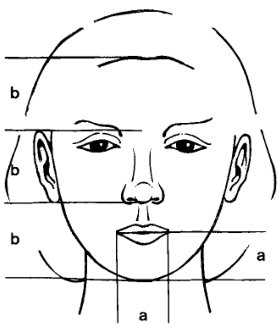

Figure 5: According to Da Vinci, the size of mouth equals the distance between parting of lips (a), whereas the distance from chin to nostrils, from nostrils to eyebrows and from eyebrows to hairline are all equal (b) and the height of the ear equals the length of the nose [6].

3.2 Feature Selection

We thus find local features and anthropometric distances emphasized by various artists in their renderings particularly useful for our analysis.

3.2.1 Local Features

These include features such as corner of the eyes, tip of the nose, etc. which are specific to a person. Many methods have been proposed based on the geometry of local features. One of the most well-known approaches to analyze local facial features is based on Elastic Bunch Graph Matching [18]. Here faces are represented as image graphs which are based on fiducial points on the face (e.g., eyes, nose, mouth corners) extracted using Gabor filters. This technique has been shown to be particularly useful when distinguishing which facial features are retained in the images.

Gabor wavelets are very robust as a feature repersentation and are biologically relevant since they mimic the behavior of visual cortex. A review of Gabor filters for face recognition can be found in [12]. Since artists often try to focus on such distinguishing features, we believe that this method is particularly suitable for our problem. In this work, we evaluate the local feature similarities as in [18].

Number	Description of the feature
1	forehead tips (left)
2	forehead tip (right)
3	forehead center
4	chin bottom
5	nose top
6	nose bottom
7, 8	points on temple (left, right)
9, 10	chin ear corners (left and right)
11, 12	points on chin (left and right)
13, 14	cheekbones (left and right)
15, 16	mouth corners (left and right)
17, 18	iris (left and right)
19, 20	left eye corners (right and left eye)
21, 22	right eye corners (right and left eye)

Table 1: List of local features

3.2.2 Anthropometric Distances

These include salient distances such as width of forehead, width of upper face, etc. Anthropometric methods have provided normative models of facial measurements along with the degree of deviation in a population [4, 5]. Since such measurements have been of interest to artists as well, the similarity of such anthropometric measurements has been one of the tools that we have employed in our analysis.

3.3 Feature extraction

(a) Local features: A set of 22 fiducial points is used to represent each face. We number them for convinience. A complete list of these is provided in Table 1. The precise location of these points is determined by registering a generic mesh on the face by determining a number of corresponding points between the face and the mesh. Gabor jets are evaluated at each of these fiducial points. A jet describes a small patch of grey values in an image around the fiducial points described above. It is based on convolution of the image with Gabor wavelet kernals corresponding to 5 frequencies and 8 orientations. Thus at each fiducial point, we have 40 such co-efficients constituting the jets. The limited localization in space and frequency of the Gabor kernals yields some amount of robustness against translation, rotation and scaling. Robustness against varying contrast is obtained by normalizing the jets.

At a fiducial point n and for a particular scale and orientation j, the corresponding jet co-efficient J_{n_j} is given by

$$J_{n_j} = a_{n_j} \exp(i\phi_{n_j}), \tag{1}$$

where a_{n_j} is the magnitude and ϕ_{n_j} is the phase.

(b) Anthropometric distances: All images are normalized with respect to scale and orientation. A set of 11 anthropometric distances characterizes each face. These distances are extracted after computing the 2D Euclidean distance between the corresponding points as obtained from registration. The complete set of these distances is provided in Table 2.

Number	Description of the feature
1	distance between forehead tips
2	distance between forehead center and chin bottom
3	distance between nose top and bottom
4	distance between points on temples
5	distance between chin ear cornors
6	distance between points on chin
7	distance between iris
8	distance between cheekbones
9	distance between mouth corners
10	width of nose
11	distance between forehead center and nose bottom

Table 2: List of anthropometric distances

3.4 Similarity Computation

We now explain the computation of similarity scores based on local features and anthropometric distances.

3.4.1 *Local Feature*

In evaluating similarities between jets J_n and $J_n^{'}$ across corresponding fiducial points n in 2 faces, we use the expression similar to the one mentioned in [19] given by

$$S_n(J,J^{'}) = \frac{\sum_j a_{n_j} a_{n_j}^{'}}{\sqrt{\sum_j a_{n_j}^2 \sum_j a_{n_j}^{'2}}}, \quad (2)$$

where $a_{n_j}, a_{n_j}^{'}$ are as defined in (1). LF similarity score s_{LF} between two portraits is evaluated as

$$s_{LF} = \frac{1}{N}\sum_{n=1}^{N} S_n(J,J^{'}), \quad (3)$$

i.e., the average of jet similarities over all fiducial points N.

3.4.2 *Anthropometric Distances*

The similarity between AD's is evaluated by converting the distance into a similarity measure as

$$s_{AD}(m,n) = e^{-\beta * d} \quad (4)$$

where d is the 2D Euclidean distance between the AD vectors $\vec{m}$, $\vec{n}$ and β is a co-efficient that is chosen suitably to obtain a discriminative dynamic range of values. In our experiements, we set β to be 5.

3.5 Optimum Feature Combination

Portrait pairs authenticated to be of the same subject by our collaborators in art history are used as *training examples* to learn PFS (i.e., image pairs depicting subjects whose identities were *known* are used for learning PFS). We fuse scores obtained from LF and AD features of these images in a way such that the resulting distribution of match and non match scores are as peaked and disjoint as possible. Towards this, we employ the following methodology.
1. We consider a convex combination of the scores from the two measures LF and AD as $\lambda * s_{LF} + (1-\lambda) * s_{AD}$, λ being varied from 0 to 1 in steps of 0.1.
2. For every λ, we evaluate the mean and standard deviation of match and non-match scores using the RANSAC algorithm [7] to prune outliers.
3. At each λ, we evaluate the Fisher linear discriminant function [3], $J = \frac{S_b}{S_w}$ where S_b is between class variance and S_w is within class variance. We choose that value of $\lambda = \lambda_{opt}$ that gives the maximum value of J.
4. The distributions of match and non-match scores, with λ_{opt} obtained in Step 3, for the combined (LF and AD) feature set are modelled as Gaussians distributions with means and standard deviations estimated from Step 2.

3.6 Validation of the Learned PFS

We perform two-fold cross validation on the set of images i.e., we divide the set of instances into two groups F_1 and F_2. In fold 1, we learn the PFS from F_1 and validate on F_2. In fold 2, we learn PFS from F_2 and validate on F_1. The mean and standard deviations of match and non-match scores from the two folds are then averaged to obtain the resulting curves shown in Figure 6. Table 3 provides the mean and standard deviation of match and non-match scores in training and validation experiments. It is to be noted that these distributions are data dependent and can change if different set of images are considered for learning.

Ideally the distribution of match and non-match scores of the validation set should be within the range of the match and non-match distributions respectively of the learned PFS. A sample of some images that were validated correctly and that were not validated correctly is shown in Figure 7.

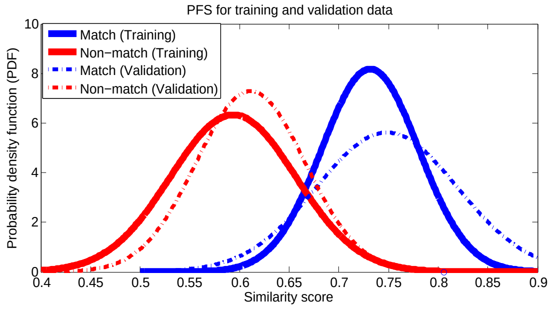

Figure 6: PFS depicting distribution of match and non-match scores. The solid lines denote learned curves (training) while the dotted lines represent validation curves.

		μ	σ
Training	Match	0.7316	0.0488
	Non-match	0.5936	0.063
Validation	Match	0.7483	0.0547
	non-match	0.6112	0.071

Table 3: Mean (μ) and standard deviation (σ) of the match and non-match scores for training and validation PFS depicted in Figure 6.

4. MODELING ARTISTS' STYLES

To understand the characteristics of artists/sitters, we consider the well-known permutation test. A permutation test (also called a randomization test, re-randomization test, or an exact test) is a type of statistical significance test in which the distribution of the test statistic under the null hypothesis is obtained by calculating all possible values of the test

Figure 7: Example images that were validated correctly/incorrectly. The first column shows a pair of images that were known to match, which the model correctly validated. The second column denotes a pair of images that were known to match which the model failed to match and the third column denotes a pair of non-match images which the model validated as match pairs incorrectly. Columns 4, 5 and 6 denote match pairs which the model validated correctly.

statistic under rearrangements of the labels on the observed data points. In the context of the present scenario, if a particular attribute is invariant across n images of a sitter S by artists $A_1, A_2, ...A_n$, then random assignment of this attribute among the n images should not alter the constructed hypothesis. For instance, let the eyes of S as depicted by A_n be attributed to the image by A_{n+1}. Since the depicted sitter is the same, it should not matter significantly if the attributes are shuffled among images of the same sitter.) Both intuitively and from artistic practices, it can be inferred that certain features prominent to a sitter are retained in different works depicting the sitter. This is more obvious in those works that are by a single artist. Permutation test helps in assessing what characteristics are same (in other words invariant) across art-works.

To test whether two groups differ significantly in a certain attribute (say, for instance, corner of the eyes or chin bottom), we set the null hypothesis that the two groups have the same average value in this attribute along the lines described in [10]. For instance, if there are X images of a sitter Y by various artists, then we can divide the set X into 2 subgroups consisting of $X1$ and $X2$ images. We then use a two sided permuation test to compute p value [8]. Consider a particular attribute (eye corner for instance) for two groups. Let the attribute values for the first group be $[s_1, s_2, ..., s_{X1}]$ and in second group be $[s_{X1+1}, s_{X1+2}, ..., s_{X1+X2}]$. The two sided permutation test is performed by randomly shuffling $[s_1, s_2, ..., s_{X1}, s_{X1+1}, s_{X1+2}, ..., s_{X1+X2}]$ and assigning the first $X1$ values, say, $[s_{(1)}, s_{(2)}, ..., s_{(X1)}]$ to the first group and the remaining $X2$ values $[s_{(X1+1)}, s_{(X1+2)}, ..., s_{(X1+X2)}]$to the second group.

For the original two groups we compute,

$$\delta_0 = \left| \frac{1}{X1} \sum_{i=1}^{X1} s_i - \frac{1}{X2} \sum_{i=1}^{X2} s_{X1+i} \right| \tag{5}$$

δ_0 denotes the variation in the attributes of sitter Y as depicted by various artists $A_1, ...A_N$ in the two groups $X1$ and $X2$. For any two permuted groups we compute,

$$\delta_s = \left| \frac{1}{X1} \sum_{i=1}^{X1} s_{(i)} - \frac{1}{X2} \sum_{i=1}^{X2} s_{(X1+i)} \right| \tag{6}$$

δ_s denotes the variation in the attributes of sitter Y after assigning attributes as depicted by $A_i, i = 1, 2, ...n$ to an image not necessarily a work of A_i.

We repeat this random shuffling of attributes among the images under consideration multiple times and count the number of times $\delta_s > \delta_o$. The proportion of times $\delta_s > \delta_o$ is the p value. This value reflects the variation of the attribute in the two groups. Smaller p denotes stronger evidence against the null hypothesis, meaning that the attribute differed considerably in the two groups. If a certain attribute showed no difference in the 2 groups, then that particular attribute can be considered as a random assigment into any of the 2 groups from the pool of all images, i.e., it does not matter to which image this attribute is associated since the average value does not change; thus it can be considered as a random assignment into any image in the pool. In such situations, the chance that δ_0 is extreme should be small (it will be extreme only if values in 2 groups differ significantly in average across the groups). At a given threshold γ, we decide that the attribute differs significantly if $p < \gamma$.

Thus, in the same sitter scenarios, we are interested in those attributes with $p > \gamma$, the attributes which are same across different works. On the other hand, for works of an artist depicting different sitters, we might be interested in knowing which attributes differed significantly, since it might provide useful cues in distinguishing sitters. However, if a certain attribute did not differ significantly in various works of an artist, it might provide some information regarding the artist's style.

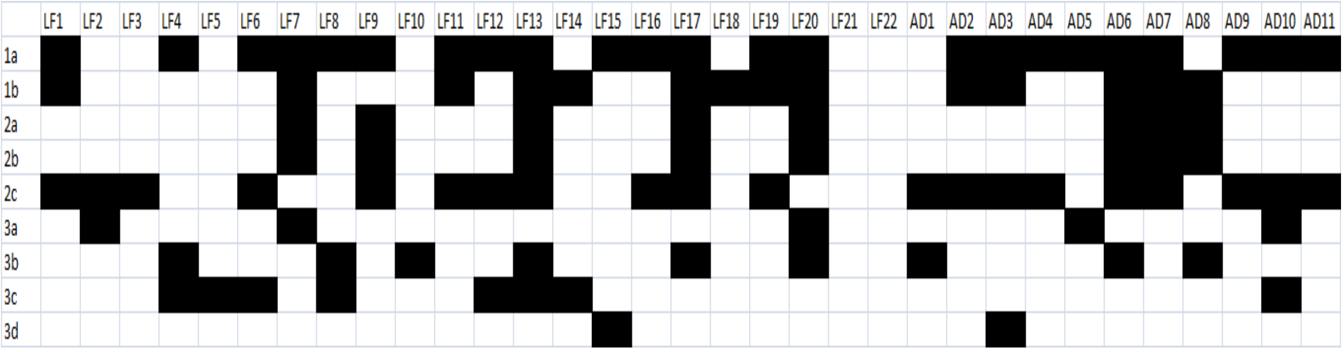

Figure 8: Particular LF and AD that are similar across art-works in cases considered. The rows correspond to various cases described in Sec 4.1; the columns denote the particular features. LF-Local feature, AD- Anthropometric distances. The numbers of LF/AD correspond to those mentioned in text in Sec 3.3

4.1 Case Studies for Artist-Sitter Combinations

For all the cases under consideration, we performed permutation test on both LF and AD attributes. Please refer to Sec 3.2 for the attributes numbered in each case. The conclusions described below are represented graphically in Fig.8.

1. **Same Sitter, Same Artist**
   a) Sitter- Innocent X, Artist - Algardi: This corresponds to five images of the same sitter by a single artist. In order to understand the importance of chosen attributes, we performed permutation test as described in Sec. 3.4. The set of LF and AD features that were similar are indicated in Figure 8 under the particular case.

   b) Sitter- Mary Queen of Scotts, Artist- F. Clouet: This corresponds to 5 images of the same sitter by a single artist. Features that were similar are indicated in Figure 8.

2. **Same Sitter, Different Artist**
   a) Sitter- Mary Queen of Scotts, Varied Artists: This consisted of 7 images by different artists. It can be noticed that the number of similar features is less than that in case 1b. This is understandable since although the sitter is same as case 1b, the artists are different, thus creating the variability.

   b) Sitter-Isaac Newton, Varied artists: This consisted of 5 images of Newton by varied artists. In this case, high p values were noticed for LF attributes 7, 9, 13, 17 and 20 and for AD attributes 6, 7 and 8.

   c) Sitter- Robert Dudley, Varied artists: This comprised of 5 images. Artists of 3 images are unknown. In this case, high p values were noticed for LF attributes 1, 2, 3, 6, 9, 11, 12, 13, 16, 17, and 19 and for all AD attributes except 5 and 8. The unusually high number of common attributes among varied artists could suggest that some of the artists might have been same or that features of the sitter were very prominent and hence captured by many artists in their renditions almost similarly.

3. **Different Sitters, Same Artist**
   a) Artist- Bernini, Varied Sitters: Attributes with high p values in this case, are indicative of certain specific styles the artist could have used to draw different regions of the face. One can notice that this number is significantly small compared to other cases where sitters are same. This is due to varied sitters considered.
   b) Artist-Kneller, Varied Sitters: Various sitters depicted in portraits of Kneller included Newton, James Scott, Kneller himself among others.
   c) Artist-Holbein, Varied Sitters: We considered about 20 images by Holbein, depicting various sitters such as Seymour, Cheseman, Anne of Cleaves, etc.
   d) Artist-Van Mierevelt, Varied Sitters: We considered about 20 images by Van Miervelt, depicting various sitters such as Spinola, De Groots, John Borlase among other portraits of Miervelt whose sitters is unknown.

4. **Different Sitters, Different Artists:**
   For this case, we pooled the entire data to consider works across as many sitters and artists as possible. It turned out that none of the attributes exhibited a high p value. This is understandable since amongst varied sitters and artists, it is unlikely to find attributes which are highly invariant.

4.2 Analysis of Case Studies

We explore answers to two questions of interest—
1) What features are specific to an artist's styles and which ones are characterisitc of a sitter?
2) What is the relation between similarity scores in the 4 scenarios of artist-sitter combinations described earlier?
We analyze the two below.

Understanding Artist Styles:
Given a specific case of artist and sitter combination, the goal here is to learn the invariant features. In case 1a, about 70% of the features were invariant. This is understandable since the artist and sitter were same. Cases 1b and 2a depicted the same sitter Mary Queen of Scotts. It can be noticed that the number of invariant features in case 2a is lesser by about 15% than case 1b since these were by different artists. However, some features such as exterior eye coner of the left eye, distance between iris, etc. were invariant in both cases. These invariant features could have been, possibly, prominent characteristics of the sitter.

Across 2a, 2b and 2c, roughly only about 36% of the features are invariant, this being significantly less than the scenario where one artist depicted one sitter. The number of invariant features further reduces in cases 3a, 3b, 3c and 3d corresponding to same artist but depicting various sitters. On an average only about 18% of the features are invariant in these cases. This is intuitively correct since the sitters are different. Features that are invariant could be typical of some artists' styles; for instance, height of the nose and left mouth corners that were invariant in case 3d, could be characteristic of Van Mierevelt's style.

Relationship between Similarity Scores under Various Scenarios:
Given the ground truth about image pairs (i.e., whether pairs match or not match), the goal of this analysis is to understand the relation between scores under the 4 scenarios mentioned earlier. Figure 9 provides a sample illustration of the distribution of similarity scores for the 4 scenarios. In evaluating these scores, we used all the 22 LF and 11 AD features. It is to be noted that scores in Figure 9 are not necessarily that of the cases considered earlier.

As can be noted, in the same sitter, same artist cases, the scores lie towards the extreme right hand side of the number line denoting the range of similarity scores. This indicates a high degree of match. The set of scores of same sitter by different artists exhibit the next highest similarity scores. Since the artists are different, these scores are lower than the previous case. Same artist, different sitters cases lie to the left of scores from same sitter, different artists cases since these correspond to non-match instances. Scores of different artists depicting different sitters fall on the extreme left of the number line, all these scores are the lowest indicative of non-match and the high degree of variability in artists' depictions.

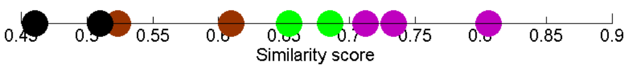

Figure 9: Distribution of similarity scores for various scenarios described. Purple balls denote same sitter, same artist scores, green balls denote same sitter, different artist scores, brown balls denotes same artist, different sitter scores and black balls denote different artists, different sitter scores.

5. CONCLUSIONS

We presented a work that explores the feasibility of computer based face analysis for portriature works. After a careful understanding of artistic conventions, we arrived at relevant features for analysis. Subsequently, using machine learning tools, we learned a feature space describing the distribution of similarity scores for cases known to match/not match and also validated the same. We also considered various combinations of artists and sitters to model artists' styles on a number of different instances. This led us to understand features characteristic of a sitter and/or artist. Future work will consider using the learned invariances to develop robust face recognition algorithms in portrait art.

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