Stylometrics of artwork: uses and limitations

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1. ABSTRACT

A number of digital image analysis techniques have been developed in recent years to address art historical questions. These techniques allow non-destructive analyses of art images that can target outstanding problems of attribution, historical ordering, and other stylistic dimensions. However, great care must be taken in designing the comparisons to which these techniques are applied. In this paper, we review recent work by our lab and by others aimed at establishing a toolbox of stylometrics, and we discuss some of the uses and limitations of these methods. We describe a technique that provides robust classification of authentic drawings by Pieter Bruegel the Elder, and we demonstrate new techniques for art historical analysis applied to the works of other masters. Specifically, we demonstrate the use of two low-level statistics (the slope of the log amplitude spectrum and color histogram correlation) to analyze the works of Picasso and Braque. Finally, we show that face detection and recognition techniques may play a useful role in the attribution of works of art. The rationale for employing vision coding-like methods (e.g., sparse coding) in stylometry is also reviewed. We conclude that generic authentication tools are unlikely to provide reliable stylometric predictions but that with careful construction of comparison sets – which we believe must be done in close collaboration with art historians – these techniques provide important predictions that can be weighed against other art historical evidence. We argue further that concurrent predictions derived from analysis of many independent dimensions of image data (e.g., color, luminance, and spatial statistics) provide the strongest evidence for digital stylometric determinations.

2. MOTIVATION

Despite decades, and in some cases centuries, of analysis, art historians continue to grapple with questions of authenticity and attribution of important works of art.[1–5] Traditionally, methods such as connoisseurship and provenance studies have provided the primary means for attributing works to particular artists. However, since at

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least the late 19th century, scientific techniques have augmented these approaches by offering objective means for investigating art and quantifying its properties.[6,7] Increasingly, non-destructive digital techniques are being used to assist art historians in making determinations about the authenticity and attribution of works of art.[5,8–11] Nevertheless, many of these techniques are still in their relative infancy, have not been tested on a diverse set of works, and, most importantly, do not address critical outstanding issues in art analysis, such as the way in which the field of conservation can benefit from mathematical tools. As digital archives of museum collections grow and become more accessible to researchers, so too grows the number of potential scientific approaches to examining these works that lie outside of the traditional framework of art historical analysis.

Here we present the use of digital stylometric tools to address several art historical problems. First, we briefly review a recent result that describes a possible method to assist art historians in the attribution and authentication of works using a high-level spatial statistical characterization of style. Specifically, we show that, using the sparse coding model of Olshausen and Field,[12,13] we are capable of discriminating between authentic drawings by Pieter Bruegel the Elder and well-known Bruegel imitations. We also present the use of two low-level image statistics (the slope of the log amplitude spectrum and color histogram correlation) as a means of exploring the differences between works of art throughout Picasso's *oeuvre*. We show that these statistics can help distinguish art in various periods of his work, and that they are particularly powerful at distinguishing representational from abstract art. Furthermore, we present a hypothetical framework for authenticating works using these statistics, and show that such a method is successful at differentiating with high confidence works by Picasso from those of Braque in the style of Analytical Cubism. Finally, we use leading face detection and recognition algorithms to explore the degree of abstraction in painted faces. We posit that face detection and recognition techniques, in a more advanced form, may be able to answer important art historical questions, such as whether a recently attributed Velazquez is in fact a depiction of the artist himself.[4] We argue that *well-formed questions* are central to the success of digital stylometric methods, and describe how digital techniques, in concert with traditional art historical analyses, can provide answers to important questions in the study of art.

3. DIGITAL STYLOMETRY

Digital stylometry can be defined as the application of digital (i.e., discrete) mathematical approaches to the quantification of style. This necessarily broad definition

Uses	Limitations
- Attribution	- Need well-formed questions
- Authentication	- Data often limited
- Distinguishing periods in art	- Can be affected by imaging process
- Quantifying "degree of abstraction"	- Often difficult to generalize beyond specific artist
- Broad topics in conservation (e.g., using face recognition to identify subjects in portraits)	- Assessments should be based on multiple tests
- Non-invasive analyses	

Table 1. Uses and limitation of digital stylometric techniques.

encompasses techniques as diverse as examining the way in which artists compress the dynamic range of luminance in natural scenes to a formal analysis of craquelure.[14–17] As noted in,[18] digital stylometry is a natural extension of preexisting techniques for the scientific analysis of art. A central component of the contribution that digital stylometric tools can make to the art world is that they provide an objective means of comparison. Table 1 describes some of the uses and limitations of digital stylometry, but this is by no means an exhaustive list. Other possible applications include medium discovery (e.g., whether a drawing was done in ink, charcoal, etc.) and face recognition, which is treated in detail below. There are also important limitations that should be considered, such as the fact that the imaging process alone can have a profound effect on the outcome of certain tests. For example, if images are obtained under different lighting conditions, this can affect the efficacy of tests that examine luminance compression or color histograms.[15,16,19,20] Determinations of authenticity and attribution can have an enormous impact on the value of a particular work of art. By utilizing objective measures to quantify stylistic properties of works of art, art historians and other researchers can provide unbiased evidence to support the attribution of a work of art to a particular artist.

4. RESULTS

Here we present results for the application of several stylometric techniques to resolved and outstanding art historical questions.

4.1 Sparse coding

We begin by presenting the results of an analysis performed on a set of secure drawings by Pieter Bruegel the Elder and a set of Bruegel imitations long thought to be authentic.[1,8] We applied the sparse coding model of Olshausen & Field[12,13] to create a set of sparse basis functions to model the higher-order statistical structure in authentic Bruegel drawings. The sparse coding model attempts to characterize images by learning an overcomplete set of not necessarily orthogonal basis functions that describe the space of images optimally according to a sparseness constraint.[12]

We demonstrated that, using a sparse coding model, we could reliably and consistently judge authentic Bruegel drawings not used for model training as more similar to other authentic Bruegels than randomly selected imitations (see[8] for a more detailed treatment). In particular, we trained a sparse coding model on a set of authentic Bruegel drawings, then measured (using kurtosis) how sparsely we could represent both authentic Bruegel drawings and Bruegel imitations. We found that the authentic Bruegel drawings were associated with consistently higher average kurtosis of the distribution of coefficients. This research opens up the possibility of using efficient coding methods to describe artistic style, and to subsequently use this information for attribution purposes.

4.2 Low-level statistics

As an example of the application of low-level statistics to art historical problems, consider the body of work of Picasso. Picasso's work can be broken into distinct periods, and these periods are marked by often drastic stylistic changes. It could then be asked: Is there a statistic (or set of statistics) that describes these stylistic differences? Over the course of his career, Picasso's work varied from representational to highly abstract. If we concentrate on the spatial statistics of Picasso's work, then a reasonable hypothesis could be that as Picasso's work becomes less representational, the statistical structure of his work becomes less like that of the natural world. One way to quantify this characteristic is using the slope of the log amplitude spectrum of an image.[21] We estimated this value for works from a set of periods of Picasso's work by sampling five square subimages from each image with side length equal to the minimum image dimension minus a small buffer, then finding the average slope of the log amplitude spectrum across all subimages. Note that this statistic has an amount of inherent dimensionality reduction (and thus some loss of information): the images were first converted to grayscale, so this statistic necessarily excludes color information, and amplitude excludes phase information in the frequency domain. As shown in Figure 1, the average slope of the log amplitude spectrum from a set of representative images from each of these periods tended to increase from values close to what one would expect for natural scenes ($\sim$ -1.4). On average, the periods whose spatial statistics were closest to those of natural scenes were the periods of

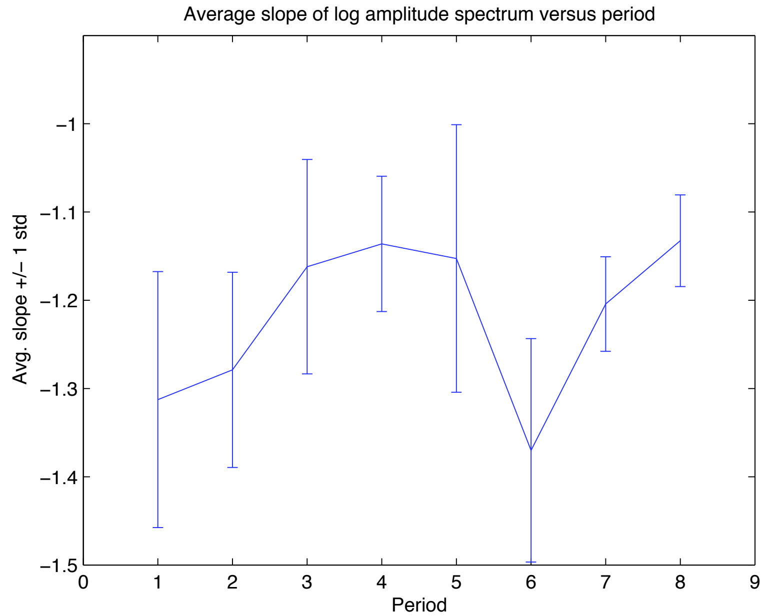

Figure 1. Average slope of log amplitude spectrum versus period $\pm$ 1 standard deviation. Periods are in order as follows: Blue Period, Rose Period, Early Cubism, Analytical Cubism, Synthetic Cubism, Interwar, Spanish Civil War-Post WWII, late works. Note the general trend of a shallowing of slope (except for the Interwar period) as Picasso's career progressed. Furthermore, the shallowest slopes correspond to Picasso's Cubist periods and late works.

Picasso's most representational work; other periods exhibited spatial statistical structure that is on average quantitatively dissimilar to the structure of natural scenes. Furthermore, a nonparametric Mann-Whitney U-test performed on the distributions of slopes of log amplitude spectra of images between periods showed that early, more representational periods were distinct from the early and Analytical Cubist periods (the Blue Period was shown to be distinct from all Cubist periods), as well as later periods.

While not a perfect means of distinguishing between representational and abstract works in Picasso's *oeuvre*, this simple spatial statistic is particularly interesting in the context of other work (e.g.,[22]) that attempts to use low-level statistics to classify broad categories. One of these low-level approaches used RGB color histograms to compare works.[19,20] We applied a similar analysis to the Picasso works studied, computing the correlation distance between the RGB color histograms for a single

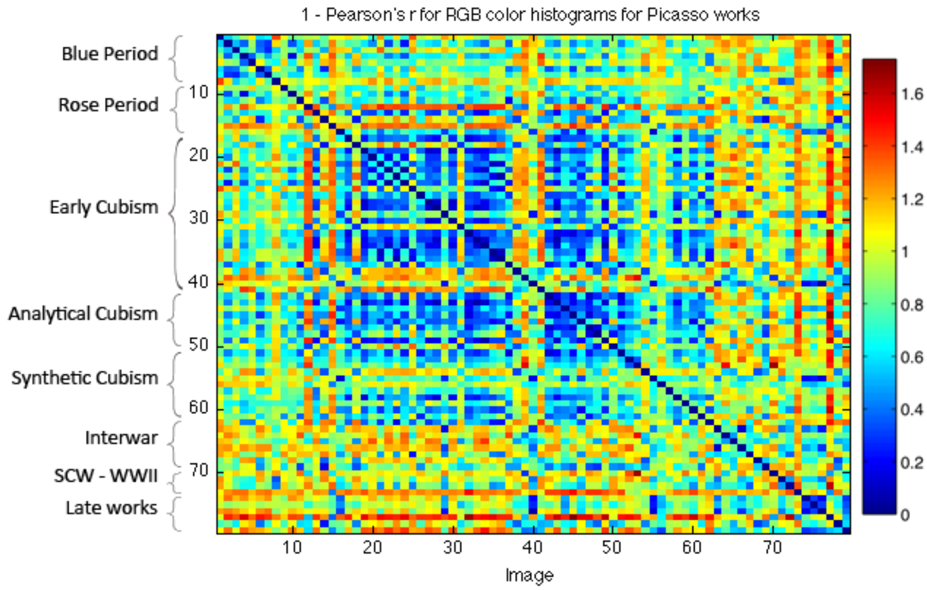

Figure 2. 1 - Pearson's r for RGB color histograms for Picasso works across the periods listed in Figure 1. For each image, histograms of RGB values were obtained by quantizing the range of values into 20 equally spaced intervals; these quantized counts were then concatenated to make a 60-dimensional vector for each image. Pair-wise correlation was then computed on these vectors. Notice the large central area where correlation distance is low (corresponding to Picasso's Cubist periods).

square section of each work (obtained as above). Figure 2 shows the dissimilarity matrix computed from these scores (i.e., 1 - Pearson's r). Despite the fact that we did not use digitizations that had been color calibrated, we find a surprising amount of intuitive structure in this matrix. Namely, the dissimilarity between works in Picasso's Cubist periods is on average quite low, as is the distance from works in his Blue Period to one another, as well as within his late works. In Picasso's Cubist periods, his works tended to have limited color palettes (with many earthy, brown tones); this appears to be reflected in our result.

We now turn briefly to a consideration of an application of low-level statistics such as these to a hypothetical art historical question. Suppose a new work were discovered in the style of Picasso's and Braque's Analytical Cubism, believed to be a Picasso. How might we use the techniques described here to assess its authenticity? Using color statistics, we could follow an approach similar to the one described in[22] and obtain a confidence estimate based on the new painting's correlation distance to other Analytical Cubist works by Picasso, given a multivariate probability distribution estimated from the "training data" (i.e., authentic Picassos). Using the amplitude spectrum approach, we could estimate a univariate Gaussian distribution given the distribution of slopes for Picasso's Analytical Cubist works. We could then, as in the multivariate case, estimate the probability that the new work came from the same distribution. The accuracy of this probability estimate depends on two factors: the accuracy of the samples (i.e., how representative they are of the underlying distribution) and how good a model the chosen distribution is for the actual distribution.

In an attempt to give concrete foundation to this admittedly hypothetical scenario, we estimate p-values for a selection of works by Braque in the style of Analytical Cubism. We obtained subimages from a set of Braque works in the same manner as above, and estimated the slope of the log amplitude spectrum for each by averaging over five subimages. Using 15 of Braque's works, we found that, using sample estimates of the mean and variance for Picasso's Analytical Cubist period from our data to estimate a normal distribution, eleven of the Braques were judged significantly different at the $\alpha = 0.05$ level (lower tail only). If we relax our significance criterion to $\alpha = 0.10$ (lower tail only), then 12 of the Braques are judged significantly different. Figure 3 summarizes these results. In concert with other analyses, such an analysis could be used to help validate a newly discovered "Picasso," if other, more traditional measures are consistent with the hypothesis that such a work is in fact genuine. Though such an analysis must be undertaken with care, we believe that an approach such as this has wide applicability.

4.3 Face detection & recognition

We use a leading face detection program[23,24] to test whether we can successfully locate faces in art images. We chose the work of three artists to examine this question. We chose work that ranged from highly representational to somewhat abstract, namely portraits by Vincent van Gogh, Diego Velazquez, and Chuck Close. All portraits were obtained as jpeg or png images downloaded off the internet or drawn from our own sources, and we made no attempt to normalize these images in any way or control for pose, lighting condition, etc. The images were chosen as a random sample of representative portraits by the artists in question (except for the Chuck Close works, which were exclusively from his "Tapestries" series). We used the demonstration software available on the Pittsburgh Pattern Recognition website.[24] We input the images indicated in Table 2 into the program and obtained confidence scores for correctly identified faces. Table 2 shows that, moving from abstract but representational to highly representational art, there is an increase in

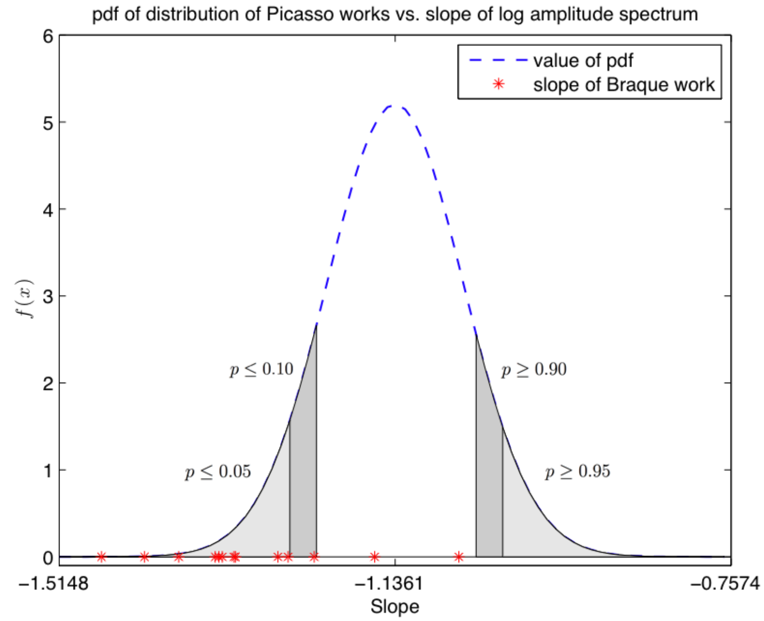

Figure 3. pdf of normal distribution estimated from slopes of log amplitude spectra for works from Picasso's Analytical Cubism period, $\mathcal{N}(-1.1361, 0.0767)$. The red asterisks indicate the slope of the log amplitude spectrum for a set of Braque works in the same style. Lines indicating confidence intervals as described in the text are shown. For a single-tailed (lower tail) significance criterion of $\alpha = 0.10$, 12 of the Braques are judged significantly different; for $\alpha = 0.05$, 11 of 15 Braques are judged significantly different.

the mean confidence score for faces. Also, both categories of more representational art exhibited significantly less variance in confidence score for portraits. Indeed, the faces in some van Gogh paintings were not identified at all. In the case of the Chuck Close portraits, all subjects' faces were depicted against a black background, and the portraits marked with an asterisk were of subjects with black skin. We believe the diminished relative contrast of the subject to the background may have resulted in lower confidence scores for these images, and present results excluding these images as well. To our knowledge, this is the first application of face detection algorithms to identifying faces in works of art. While it is not necessarily surprising that algorithms designed for detecting (human) faces in photographs would perform better on more representational art, the implications of the success of this approach are perhaps somewhat subtler. Since face recognition appears to be such an innate mechanism in the human brain,[25] systems such as the one used may shed light on

Portraits by van Gogh	Confidence Score
Self-portrait dedicated to Gaugin	0
Self-portrait - Autumn 1887	2.9
Self-portrait with felt hat	*no correct id*
Self-portrait (1889)	1.6
Portrait of Joseph Roulin	0.6
Portrait of Dr. Gachet	*no correct id*
Portrait of Dr. Rey	3.4
Mean/variance for artist:	1.7/2.11
Portraits by Velazquez	Confidence Score
Portrait of Juan de Pareja	2
Portrait of Don Diego de Acedo	2.5
Portrait of the Count of Olivares	3.3
Portrait of Philip IV (1624)	2.5
Portrait of Philip IV in armor (1628)	2.8
Portrait of Pope Innocent X	3.1
Portrait of a man	3.4
Mean/variance for artist:	2.8/0.253
Portraits by Chuck Close	Confidence Score
Brad	4.9
*Ellen**	0.5
Self-portrait (6)	2.9
Self-portrait/Color	2.4
Self-portrait (14)	2.8
Kate	2.4
*Lyle**	2.1
Philip Glass State II	4.1
Kiki	2.6
Mean/variance for artist:	2.744/1.528
Mean/variance for artist (excluding *):	3.157/0.930

Table 2. Confidence scores for portraits by the artists listed, obtained using the online demo from Pittsburgh Pattern Recognition.[24] Mean and variance for the scores for each artist are also provided for comparison.

the threshold between representations of faces that are immediately recognized as such by the brain and representations that require a great deal of imaginative effort to "see" as a face – in essence quantifying their "degree of abstraction."

Furthermore, abstract faces are particularly interesting in the context of psychological priming.[26] Examples of this in art are the portraits of Arcimboldo (1527-1593), who is known for having constructed likenesses of his subjects using objects like fruits, vegetables, and flowers. Humans can easily perceive faces in these images, especially since they occur in the context of helpful pictorial cues like the upper part of a torso and a familiar portrait setting. It is therefore interesting to ask how well the software used above fares on this task – one that arguably possesses a great deal more abstraction between the subject and its depiction than any of the works tested previously. However, recognition of the arrangements of objects in the works of Arcimboldo as faces is a trivial task for humans. As Table 3 indicates, the software fares quite poorly on these images, though it does identify two with positive (albeit weak) confidence scores. In most of these images, spurious patches were identified as faces, often with higher confidence scores than the actual face area. Since studies (e.g.,[25]) suggest that face detection relies a great deal on low-frequency information, we also blurred each Arcimboldo image with a Gaussian filter of 8 pixel radius to obtain a low-pass filtered image of each painting, and performed the same tests again. The performance of the algorithm was better in two cases, but worse in several others. While these low-pass images are more direct representations of the low-frequency components of face images, it seems that useful information was also lost. The success of this software at all is remarkable, but points to its reliance on specific arrangements of pixel values – and the fact that it possesses none of the higher-level cognitive reasoning power that allows humans to perceive a face, even in places where none truly exists.

A further problem related to face detection is that of face recognition. We applied the well-known Fisherfaces algorithm[27] to an outstanding art historical problem. The Metropolitan Museum of Art recently attributed a portrait to Velazquez,[4] yet the subject of the portrait is not definitively known. Using Fisherfaces, we attempted to verify whether the person depicted is the same figure depicted in the well-known *Surrender of Breda*, and whether this person is in fact Velazquez himself. Unfortunately, this technique was unable to reveal a positive result for a number of reasons. First, while Fisherfaces ultimately deals with projections of images into subspaces that (ideally) provide maximal between-category separation, the technique uses actual grayscale pixel values as inputs. Thus, it does not work well for images with pose variation, since there would be little expectation of high correlation between specific pixels, even for in-category images. Most face recognition algorithms restrict

Work	Confidence Score	Confidence Score for blurred image
Vertumnus	-0.5	0.3
The Jurist	0.9	0.2
The Librarian	*no correct id*	*no correct id*
Winter	*no correct id*	*no correct id*
Spring	-0.1	*no correct id*
Summer	*no correct id*	*no correct id*
Autumn	0.6	1.4
Mean/variance for artist:	0.225/0.409	0.633/0.443

Table 3. Confidence scores for Arcimboldo paintings.

recognition to a particular pose (usually frontal) and perform well in this context,[27] and thus this technique seems appropriate for art images only in this limited circumstance. The task of face recognition is further complicated by a paucity of data. In order to verify the identity of a person in an image with any degree of accuracy, it stands to reason that one requirement is to have several positive exemplars of the person in question. Furthermore, to create optimal separation in the Fisherfaces setting, there should also multiple exemplars in the comparison classes (i.e., the classes present only in training). For art images, both of these requirements are often difficult or impossible to meet. While our experiments in face recognition were unsuccessful, we believe that with further development, face recognition tools could be widely applied to outstanding questions, particularly in the conservation of art. As the Velazquez example above demonstrates, the ability to correctly identify the subjects of portraits is of significant value to art historians and conservators. Furthermore, the identifications themselves provide evidence that could assist in the attribution of a work to a particular artist.

5. RELATIONSHIP TO VISION CODING

Art – representational or not – consists of renderings of the visually perceptible. Concordantly, important questions can be asked about the process of the formation and execution of a work of art. First, how does an artist *see* the world? How does an artist take an internal representation of the world (i.e., perception) and translate this into a recreation of it? Artistic style is made up of the regularities that exist in the rendering of a work of art, and for each artist, there may exist a quantifiable representation of these regularities. Stylometric tools are based largely on an understanding of the visual processes that give rise to our perception of the

Table 4. Partial checklist of dimensions of style addressed by digital stylometric techniques.

Image dimensions
- High-level spatial statistics
- Low-level spatial statistics
- Luminance statistics
- Color statistics
- Face identification, pose of sitter
- Brushstroke analysis
- Spatial composition

natural world – and by the realization that what we call art is created by individuals that all perceive the world in essentially the same way. Nevertheless, it is not easy to disentangle differences in perception from differences in execution, and it may be these very differences in perception that are fundamental in the creation of an individual style.[28]

6. EXPERIMENTAL CONSIDERATIONS

There are a number of experimental considerations that should be taken into account when applying stylometric techniques to the analysis of visual art. For example, conclusions that can be generalized for one period of an artist's work may not hold for another period. It is also important that questions of style should be well formed and fairly constrained. Stylometric techniques are most apt to deal with situations where the notion of stylistic similarity can be reduced to straightforward assertions, e.g., comparing a known work by a particular artist to sets of works by the same artist, or attempting to authenticate a work by comparing it to known works by a particular artist. Perhaps the most critical consideration of all is that any one particular piece of evidence should not necessarily be used to make general assertions. Table 4 gives a (partial) list of image dimensions that should be considered when assessing style, some of which were presented here. Particularly in the world of art history, where the amount of available data is usually quite limited, one must gather evidence from many different sources to support conclusions about authenticity, attribution, etc. Therefore we support an approach to digital stylometry that relies heavily on interaction with art historians, traditional primary and secondary art historical source material, and a suite of stylometric tools that can analyze digital representations of works of art from many different statistical perspectives.

7. CONCLUSIONS

We have presented the use of several digital stylometric approaches, ranging from high-level spatial statistical characterizations to face detection and recognition. In particular, we first demonstrated the application of a sparse coding model to problems of art attribution. This approach is apt for analyses that seek to take the range of higher-order statistical structure in works of art into account. We also provided examples of low-level statistics – the slope of the log amplitude spectrum and color histogram correlation – as a means of describing the similarity of works of art. A framework for using these statistics to judge the confidence of attribution of works of art to a particular artist was also discussed. Finally, we presented what we believe is the first application of face detection and recognition algorithms to works of art. Although this approach is in its infancy, we believe it has applicability in the field of digital stylometry, and provided an example where more sophisticated face recognition methods would prove highly useful in answering an important outstanding art historical question. We also addressed the connections between vision coding and the investigation of statistical regularities in art. The experiments presented here, as well as their predecessors cited above, demonstrate that digital stylometry, while still an emerging field, has serious potential to serve as an important analytical tool to supplement traditional art historical analyses by providing objective, quantifiable means of assessing artistic style.

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