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Art Authentication from an Inverse Problems Perspective

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Abstract: In art authentication and attribution, the overall goal is to confirm whether a particular piece of art $\mathcal{P}$ is what it is claimed or thought to be. The claim $\mathcal{O}$ is likely to be an original work by a particular artist $\mathcal{A}$. Consequently, the essential *modus operandi* in art authentication is the collection of information $\mathcal{I}_\mathcal{P}$ about $\mathcal{P}$ to compare with the known (and, possibly, yet to be determined) information $\mathcal{I}_\mathcal{O}$ and $\mathcal{I}_\mathcal{A}$ about $\mathcal{O}$ and $\mathcal{A}$. The art $\mathcal{P}$ is often a painting, which is the current assumption, however, it can be a sculpture or pottery, in fact any artwork or antiquity, and, occasionally, a tapestry or a tablecloth.

The connection to inverse problems comes via

(a) the collection of the information $\mathcal{I}_\mathcal{P}$ and $\mathcal{I}_\mathcal{O}$, (i.e. the collection of information about the work in question, and about securely provenanced works by the artist in question),and

(b) the optimization of the comparison of $\mathcal{I}_\mathcal{P}$ with $\mathcal{I}_\mathcal{O}$ and $\mathcal{A}$ in order to have a strategy that maximizes the confirmation that $\mathcal{P}$ is a forgery when that is the situation.

In one way or another, (a) will mostly involve the recovery of information from indirect measurements, such as spectroscopic analysis or chemical analysis. It can be quite qualitative, like a visual assessment of how the paint has been applied in terms of brush stroke geometry (stylometry), or quite complex quantitatively, like the non-destructive spectroscopic determination of the composition of the white paint in the painting. From an inverse problems perspective, (b) can be viewed as an identification protocol: What items, listed in $\mathcal{I}_\mathcal{O}$ and $\mathcal{I}_\mathcal{A}$, would be the most difficult for a forger to reproduce and easy for the authentication to detect. This is a special type of inverse problem in that one does not aim to recover all the possible information hidden in $\mathcal{P}$, but just some key features which allow $\mathcal{P}$ to be quickly identified as a forgery or to increase the probability that $\mathcal{P}$ is in fact $\mathcal{O}$.

From an image analysis and inverse problem perspective, $\mathcal{P}$ is an indirect measurement (a cumulative chronological summary) of all the things that the artist (actual or forger) did in making the painting under investigation - choice of the canvas and paints, the order in which the paints were applied, the techniques and geometry of how the paints were applied. Consequently, $\mathcal{I}_\mathcal{P}$ is not only a compendium of specific features, such as canvass type, paint application (geometry) and composition, paint application, but also key features in the chronology of its execution, such as the order in which things were performed and the effect of the passage of time on components, in that white paints or canvases, made with more or less identical components, will have deteriorated to different states after different time intervals.

Consequently, focussed subsets of features $\mathcal{F}_\mathcal{P}$, $\mathcal{F}_\mathcal{O}$ and $\mathcal{F}_\mathcal{A}$ of $\mathcal{I}_\mathcal{P}$, $\mathcal{I}_\mathcal{O}$ and $\mathcal{I}_\mathcal{A}$, respectively, are all that are required to support the decision making. Now, for the identification of the order in which the features are utilized, specific details about the artist $\mathcal{A}$ and $\mathcal{O}$ become crucial prior information. From this perspective, the stylometry of digital images of paintings is proving to be useful and rapid in performing the initial comparison. For forgeries, the decision making is finalized the moment a falsification occurs. Consequently, in authenticiation, the goal is to order the $\mathcal{F}_\mathcal{P}$ so that, when anticipated, falsification occurs sooner rather than later. Because of the inverse problem nature of the recovery, some form of stabilization must be utilized. It is often performed by using key features (signatures, fingerprints).

The aim and goal of this paper is a discussion of the mentioned connection between art authentication and inverse problems concentrating on stylometry. A rapid initial test, based on the singular value decomposition of an image of a painting, is proposed for deciding whether $\mathcal{P}$ is in fact $\mathcal{O}$.

Keywords: *art authentication, inverse problems, joint inversion, boosting, feature selection, singular value decomposition*

1 INTRODUCTION

As mentioned, art authentication involves two interconnected activities:

(i) the collection of subsets of appropriate features $\mathcal{F}_\mathcal{P}$, $\mathcal{F}_\mathcal{O}$ and $\mathcal{F}_\mathcal{A}$ about $\mathcal{I}_\mathcal{P}$, $\mathcal{I}_\mathcal{O}$ and $\mathcal{I}_\mathcal{A}$, respectively, and

(ii) the decision about the order in which this information is utilized to establish that either $\mathcal{P}$ is a forgery of $\mathcal{O}$ or to accumulate evidence that $\mathcal{P}$ might in fact be $\mathcal{O}$.

With respect to the information $\mathcal{F}_\mathcal{O}$ and $\mathcal{F}_\mathcal{A}$ already available about $\mathcal{O}$ and $\mathcal{A}$, the order in which the corresponding information $\mathcal{F}_\mathcal{P}$ is collected about $\mathcal{P}$ will be influenced by whether it is already available, the ease with which it can be obtained, the cost and the time required.

Legal considerations can require additional confirmation to increase the probability that the initial assessment is correct that $\mathcal{P}$ is assessed to be a forgery, rather than only a copy or a misattribution. The inversion strategy of *"joint inversion"* (Haber and Oldenburg (1997)) underpins how this should be performed, in that the additional features (e.g. paint composition for different colurs, canvass materials, brush strokes) chosen to test should be quite distinct from (*"orthogonal to"*) that utilized in the initial assessment. This involves checking whether there are in fact other distinct features which also support a falsificaton assessment.

In a way, as explained in further detail below, the motivation for and the conceptualization and application of "joint inversion" is implicit in the methodology proposed by Irfan et al. (2008) which stresses the need for multiple visual features when assessing authentication and attribution. This is formalized in Al-Ayyoub et al. (2011) as a boosting methodology for visual texture classification and is validated using the drip paintings of Jackson Pollock. A variety of machine learning protocols have been proposed by various authors including Hothorn and Lausen (2003a,b); Zhao et al. (2009); Lyu et al. (2004); Johnson et al. (2008); Hughes et al. (2010)

2 ON THE RECOVERY OF THE FEATURES $\mathcal{F}_\mathcal{P}$ AND $\mathcal{F}_\mathcal{O}$

For paintings, features can be categorized in terms of how they are determined as highlighted in the equivalence classes listed below. As a consequence of classifying features in this way, a direct link to inverse problems is established, as, methodologically, a feature now corresponds to the recovery of some specific information from indirect measurement of some specific information (geometric patterns, material properties) about the phenomenon of interest (a particular painting).

EC-1. **Stylometry.** Geometric encapsulations of the visual structure of a painting recovered using various high resolution image analysis techniques (Lyu et al. (2004); Al-Ayyoub et al. (2011)). It represents an explicit feature characterization (fingerprint) of the artist and, because of its non-destructive nature and the sophistication of computer image analysis, has become an emerging methodology the potential of which is being explored.

EC-2. **Non-Destructive Testing.** Non-visual electromagnetic imaging, such as near infrared (NIR) and Raman, can again be utilized either in the fingerprint manner of stylometry to record the pattern of how the materials in a painting respond to a particular electromagnetic stimulus or to identify the presence or absence of some particular chemical in the paints, frame or canvas. However, spectroscopic analysis is something performed on small samples (destructively) taken from a larger painting.

EC-3. **Destructive Testing.** Such tests are avoided unless an alternative cannot be identified. Usually, such tests, using minute samples, are utilize to determine the composition of the paints, frame or canvass. With the wide availablity and reliability of non-destructive testing, which has became an integral part of modern science, driven by computer controlled instrumentation such as modern spectromemters, the need for destructive testing has decreased. The need for destructive testing also arises when restoration of an original painting is required, in order to maintain a high level of authenticity.

For the discussion below, the focus will be about how, for actual art authentication scenarios, the application and utilization of the above feature recovery equivalence classes have yielded insight about, performed authentication and contributed to attribution. However, the emphasis will be stylometry and its formalization via singular value decomposition (SVD).

2.1 Stylometry and the Jackson Pollock drip paintings

Because it is easily performed, non-destructive and cost effective, computer image analysis of paintings has become a very popular technique in art authentication and attribution. The underlying assumption is that the stylometry of a painting is potentially a unique identifier of the artist who performed the painting in that even a skilled forger cannot exactly produce the styloymetry of the painting being forged (Holmes and Kardos (2003)), since a forger does not know exactly the order in which the artist applied the paint and how the artist conceptualized what he was aiming to achieve. The creativity with which the artist painted the original is different from that of the faker in that the faker is trying to accurately reproduce a pattern which formally can be viewed as an approximation. Consequently, the performance of stylometry can be put on a more rigorous quantitative footing by applying error analysis ideas. As with all techniques utilized in art authentication, the need to use a representative set of securely established data is required.

The key step then becomes how to define the error. Since, formally, a digital image is a matrix (or a composite of matrices), singular value decomposition represents, because of its intrinsic coordinate free nature, a framework in which to assess the error between an original and the supposed original. An SVD analysis is a quite natural way in which to explore the structure in an image as it represents the image as a sum of rank-one matrices with their importance weighted by the decreasing sizes of the singular values.

The advantage of this approach is that the stylometry of an artist can be determined on the basis of similar paintings which do not include the original for which the painting under investigation is claimed to be.

Even though the above-mentioned assumption is not perfect, it has been established by Lyu et al. (2004); Irfan et al. (2008) that, by utilizing bagging, boosting and machine learning techniques (Hothorn and Lausen (2003a,b); Zhao et al. (2009)), stylometry is able to correctly classify original and fake Jackson Pollock drip paintings, on the proviso that the comparative data set contains enough securely provenanced works to be statistically relevant.

In order to motivate and validate stylometry as an appropriate tool to perform art authentication, a non-trivial challenge is required, such as comparing originals and fakes of Jackson Pollock's drip paintings. It is not sufficient to validate stylometry on paintings for which it is obvious, after a simple visual inspection of an original and a fake, that the fake is different stylistically from the original.

Lyu et al. (2004) use wavelet statistics as their machine learning protocol. They note that the ready availability of high-resolution digital scans has heralded in a new approach to authentication and attribution. Quite importantly, such techniques can also be utilized for the analysis and classification of craquelure, the crack lines that appear over time in a painting.

2.2.1 *SVD rank-one image representation comparison procedure*

Let $M_{\mathcal{P}}$, $M_{\mathcal{O}}$ and $M_{\mathcal{A}}$ denote the square $N \times N$ digital image matrices, of the same resolution, of the $\mathcal{P}$, $\mathcal{O}$ and $\mathcal{A}$, respectively, and their corresponding SVDs by

$$M_{\mathcal{P}} = U_{\mathcal{P}}\Sigma_{\mathcal{P}}V_{\mathcal{P}}^T, \qquad M_{\mathcal{O}} = U_{\mathcal{O}}\Sigma_{\mathcal{O}}V_{\mathcal{O}}^T, \qquad M_{\mathcal{A}} = U_{\mathcal{A}}\Sigma_{\mathcal{A}}V_{\mathcal{A}}^T, \tag{1}$$

where, with $\mathcal{I} = \mathcal{P},\ \mathcal{O}$ or $\mathcal{A}$, the matrices $U_{\mathcal{I}}$ and $V_{\mathcal{I}}$ are the orthogonal matrix components in the decomposition and $\Sigma_{\mathcal{I}}$ the diagonal matrix components of singular values. Since the matrices $U_{\mathcal{I}}$ and $V_{\mathcal{I}}$ consist of column vectors with vector components $u_{\mathcal{I},k}$ and $v_{\mathcal{I},k}$, respectively, the above SVD decompositions can be rewritten as the following sum of rank-one matrices weighted by the decreasing sizes of the corresponding singular values $\sigma_{\mathcal{I},k}$

$$M_{\mathcal{I}} = \sum_{k=1}^{N} \sigma_{\mathcal{I},k} u_{\mathcal{I},k} v_{\mathcal{I},k}^T, \qquad \mathcal{I} = \mathcal{P},\ \mathcal{O},\ \mathcal{A}. \tag{2}$$

Once, for given $M_{\mathcal{P}}$, $M_{\mathcal{O}}$ and $M_{\mathcal{A}}$, the corresponding SVD rank-one matrix decompositions (2) have been determined, the first step is not the comparison of the rank-one matrices, but the sizes of the corresponding singular values $\sigma_{\mathcal{I},k}$. If there is not a similar decay in the sizes of the $\sigma_{\mathcal{I},k}$ for two separate choices for $\mathcal{I}$, then one has an immediate confirmation not only that the choices for the $\mathcal{I}$ do not agree but also that the rank-one matrix components see the difference.

The task then becomes one of characterizing what that particular rank-one matrix component identifies about the two choices being compared.

In a way, one can conceptualize the rank-one matrix SVD decomposition of an image as being an abstract characterization of how the painting was performed and the components and techniques involved in doing the painting.

Such rapid testing, which tends to smear out the finer detail in a painting, can, when required, be coupled with wavelet analysis, the potential of which has been investigated by Johnson et al. (2008). The advantage of the wavelet analysis is that it directly captures the finer detail in a painting.

2.2 Non-Destructive Testing - Spectroscopic signatures

The great appeal of spectroscopic analysis is that it is non-destructive, inexpensive and rapid to implement, and different modalities (near infrared (NIR), Raman) are available depending on the circumstances. However, their accuracy and reliability depend heavily on the algorithms utilized to identify the presence or absence of a signature of interest (Anderssen et al. (2011)).

Formally, spectra can be viewed as images obtained using a different electromagenetic wavelength range. Derivative spectroscopy represents a way of using the visual structure of the spectra to recover information.

Characterization of the optical and chemical properties of pigments and dyes on works of art is important for historical knowledge and fundamental to the practice of conservation (Gautier et al. (2009)).

The technology developed for art authentication and attribution also has implications for utilizing new art forms such as artworks that contain daylight fluorescent colorants (Hinde et al. (2013)). The complex dye formulations employed in daylight fluorescent pigment manufacture raise several implications for the display and treatment of this modern palette.

Information obtained from pigment and dye analysis can provide insight into the dating and origin of an object, indicate the original color and appearance, direct conservation treatment, and suggest mechanisms of deterioration. Non-destructive techniques have been developed for pigment analysis such as checking on the composition of white paints. Scanning electron microscopy is useful for identifying Titanium Dioxide whereas Raman spectroscopy is one of the few analytical techniques which can distinguish between the anatase and rutile forms of the pigment. Anatase was commercially available titanium dioxide produced from 1913, whereas rutile was developed after the Second World War. (Laver, 1997). Gautier et al. (2009) identify anastase at Raman bands of 143, 396, 516 and 639cm^{-1} and rutile at 143, 232, 446 and 609cm^{-1}.

Another aspect of non-destructive testing is the viewing of subsurface layers which can reveal drawings that are hidden beneath scattering such as the primary layers of paint. The laser speckle contrast method (LSCI) (Miles et al. (2008)) has proved to be useful in exploring for hidden structure which might be unknown to a forger or is a reminant on the canvas that the forger has used.

2.3 Destructive Testing - Direct Chemical Analysis of paints

Even when it is necessary to remove paint samples from a painting, the actual testing tends to be non-destructive for the reasons listed in the previous subsection. This is a direct reflection of the growing sophistication of non-destructive testing and its wider adoption in art authentication and attribution.

Taking white paint as the example, if the white paints contain quite different components (e.g. titanium dioxide in its rutile form and zinc white, or zinc white or lead white) then a visual comparison of their NIR spectra is all that is necessary to confirm that they are different, though the use of derivative spectroscopy could be utilized to further highlight the difference. The essence here is again a simple presence and absence scenario.

When the paints have been made with similar components, then a quantitative analysis of the spectra will be different. Now, specific information must be recovered such as the proportional presence of specific components. Methodology such as partial least squares, singular value decomposition or derivative spectroscopy are routinely used to determine the proportional presences of some specific component. Derivative spectroscopy has been proposed and utalized to recover key signatures of interest Anderssen et al. (2011).

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