Wavelet Analysis for Authentication[1]

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Abstract

In this paper we present some recent results in using a multi-scale, multi-orientation decomposition analysis (e.g., wavelets) of high resolution digitized versions of drawings and paintings as an aid to authentication. Our preliminary results indicate that various statistics acquired from the wavelet decomposition of a work seem to provide a "digital signature" of the artist, in the sense that the statistics of works of a given class by the same artist cluster together, while remaining apart from imitations.

1. Introduction

Digital techniques (i.e., computational techniques derived from digital image processing) increasingly are being seen as having the potential to play a significant role in the study of the visual arts. It is now relatively simple to capture digitally at great resolution a variety of artistic media. For example, highly faithful digital representations of paintings and drawings are readily obtained via extremely high definition digital photography. Handheld laser scanners make possible the capture of three-dimensional works. This technology, which, day by day, is only improving in terms of resolution and ease of use, has the effect of placing the "plastic arts" (by which we mean painting, drawing, and objects) within the domain of the computer and thus, within the range of the computer scientist and mathematician. As a result, the computational toolkits of these scientists are beginning to play an important role in the investigation of the plastic arts, for art historical research as well as the forensic side of this work that is authentication (see e.g., [9]).

In this paper we will present some preliminary results along these lines. In particular, we will show that the mathematical tools of multiresolution analysis, more specifically, the use of a multiscale and multiorientation analysis (commonly referred to as "wavelets") shows promise in the realm of paintings and drawings as a means of deriving a quantitative signature of an artist's style. Through the application of these techniques to high resolution digital images of the works of interest we are able to derive a number of statistics from a given work that comprise a set of feature vectors summarizing the work. A "good" set of statistics will be such that the feature vectors from secure works of a given artist cluster together while simultaneously remaining separate from feature vectors extracted from works by other artists.

Our approach, first announced in [6], is analogous to a mixture of techniques used in *stylometry*, which is the study of quantification of literary style, most famously used in settling questions of disputed authorship (see e.g., [4]) with recent work in distinguishing between real and doctored photographs [3]. We believe that the method presented herein holds promise and are actively seeking to improve and apply it in new venues and to new corpuses. As indicated in [6], the technique can also be used for the analysis of paintings.

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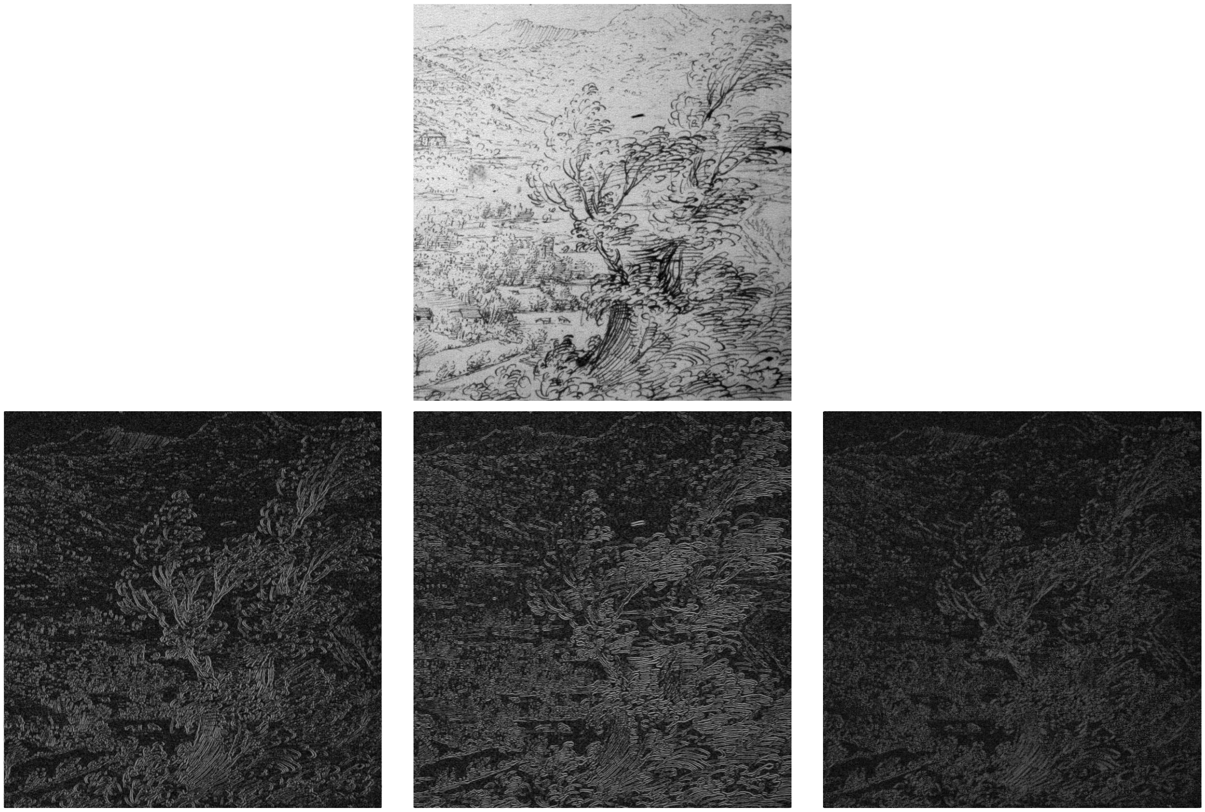

Figure 1: Visualization of wavelet data. Top: Detail from *Mountain Landscape with Ridge and Valley* (ca. 1552), by Pieter Bruegel the Elder. Bottom (from left to right): magnitudes of the subsampled coefficients of the first scale of the wavelet analysis at vertical, horizontal, and diagonal orientations.

In what follows we include a brief introduction to the multiresolution approach necessary for explaining the derivation of the feature vectors. This is presented in the context of an analysis of a new data set of ten drawings comprised by eight secure drawings of Pieter Bruegel the Elder and two imitations.

2. Image Analysis via Wavelets

Our search for a quantitative stylistic signature derives from a mathematical analysis performed on digital representations of original works. Wavelets enable the extraction of information regarding the density and orientation of linear elements in the work and thus effectively ignore the palette of the artist. For this reason we work exclusively with grayscale digital versions of the originals. For our Bruegel test set we begin with color slides of ten drawings which are scanned at 2400 dpi and then converted to grayscale by the standard technique of converting the RGB data into luminance and chrominance data and keeping the luminance. The grayscale images are then prepped for analysis by cropping a central $2k \times 2k$ pixel grid.

2.1 Methodology: The Filterbank approach. For analysis we use a particular *filterbank* decomposition of the digital representations. This results in the acquisition of image statistics corresponding to data of certain *orientations* at different *scales* - hence the terminology of *multiorientation-multiscale analysis*. In particular, our decomposition is based on the use of *separable quadrature mirror filters* (QMFs) [10, 8]. Separability means that two 1-D filters are used separately (but consecutively) on the rows and columns of the image to generate a 2-D

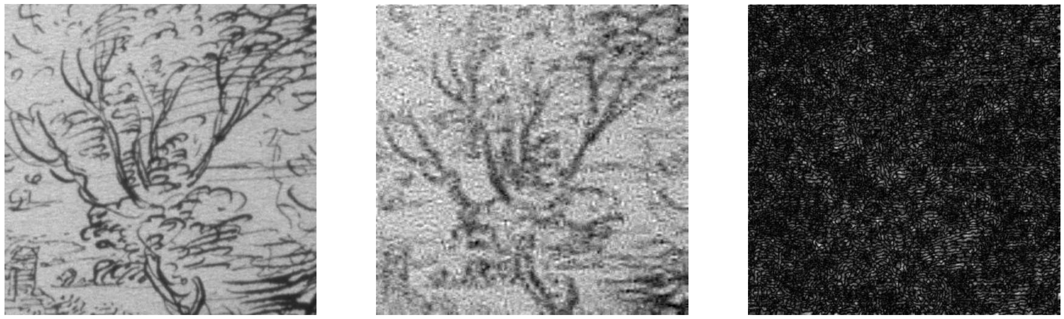

Figure 2: Illustration of predictability. The leftmost figure is a small detail from *Mountain Landscape with Ridge and Valley* (ca. 1552), by Pieter Bruegel the Elder. The center figure shows the "predicted reconstruction." The rightmost figure is the difference between leftmost and center. A perfect match would give a pure black square as the difference.

analysis. The QMF is a particular pair of lowpass (L) and highpass (H) convolution filters, the former achieves a smoothing of the signal, while the latter returns the detail. When applied in all four combinations, first across each row and then down each column, the result is the extraction of the *diagonal* (HH), *horizontal* (HL), *vertical* (LH) and *lowpass* (LL) bands. Subsequent scales are created by subsampling the lowpass by a factor of two and recursively filtering. The vertical, horizontal, and diagonal subbands at scale $i = 1, ..., n$ are denoted as $V_i(x, y)$, $H_i(x, y)$, and $D_i(x, y)$, respectively.

A picture is worth at least one thousand words (and maybe as many equations), so, in Figure 1 we show the wavelet decomposition using a detail from *Mountain Landscape with Ridge and Valley* (ca. 1552) by Pieter Bruegel the Elder, (catalog entry #4 in [7]). We have heightened the contrast in the images to help clarify the discussion. Consider the far right image of the bottom row which gives a visualization of the vertical elements. Generally speaking, regions of white, no matter how small, indicate regions in the original image containing vertical linear elements. This is most apparent in the clear delineation of the vertical lines making up the trunk of the tree in the foreground. While these vertical elements are prominently displayed, the obvious horizontal elements (e.g., the left-right lines indicating much of the leaf work in the tree) are virtually invisible here. Conversely, the horizontal elements represented in second image emphasize the leaf work while neglecting most of the linear elements composing the trunk of the tree.

2.2 Construction of the Feature Vectors. The wavelet decomposition gives the raw data from which we construct the associated feature vector. For each sub-block the feature vector will be a 72-dimensional vector that can is the conjunction of two separate although not unrelated (i.e., uncorrelated) 36-dimensional vectors. Our construction follows that used in [3]. The first 36-dimensional piece is simply a vector of marginal statistics derived from each of the three orientations at the first three scales of analysis. In the notation above, we compute the *mean, variance, skewness,* and *kurtosis* for the individual distributions (ranging over all (x, y) of $V_i(x, y), H_i(x, y)$ and $D_i(x, y)$ for $i = 1, 2, 3$.

In order to capture the higher-order correlations that exist within this image decomposition, these coefficient statistics are augmented with a set of statistics based on the errors in an optimal linear predictor of coefficient magnitude. They may be thought of as a measure of compression of the image block. Following [1], we measure the degree to which the subband coefficients are correlated to their spatial, orientation and scale neighbors. In order to do this, for a fixed orientation and scale we employ an iterative brute-force search (on a per subband and per image basis) for the optimal (in terms of mean squared error) linear predictor built on a set of seven neighbors.

For example, consider the vertical band at scale i, $V_i(x, y)$. We constrain the search of neighbors to a 3×3 spatial region at each orientation subband and at three scales, namely, the neighbors $V_{i+j}(\frac{x}{2^d} - c_x, \frac{y}{2^d} - c_y)$ where

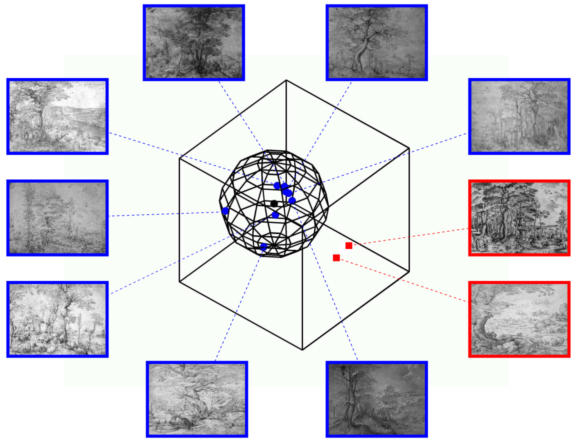

Figure 3: Results of applying MDS to the clouds of points comprising the sets of full feature vectors. Drawings are numbered according to [7].

$j, d = 0, 1, 2$ and $c_x, c_y \in \{-1, 0, 1\}$ [2]. Let $\vec{V}$ contain the coefficient magnitudes of $V_i(x, y)$ strung out into a column vector, and the columns of the matrix Q contain the chosen neighboring coefficient magnitudes. The linear predictor then takes the form, $\vec{V} = Q\vec{w}$, where $\vec{w} = (\, w_1 \quad \ldots \quad w_k \,)^T$, contains predictor coefficients determined by minimizing the quadratic error function $E(\vec{w}) = [\vec{V} - Q\vec{w}]^2$.

Figure 2 provides a visualization of what is captured by the linear predictor. The leftmost image is the original detail (of a secure Bruegel). The center image is the reconstruction of the predicted image[3] and the rightmost image shows the difference between the reconstruction and the original. We like to think of the reconstruction as providing a coarse estimate of the figure - in this case, the rough outline of a tree, so that in essence, the difference between this "generic" tree and the original is where we see the style of Bruegel the Elder.

Once the full set of neighbors is determined the mean, variance, skewness, and kurtosis are collected from the errors of the final predictor. This entire process is repeated for each oriented subband, and at scales $1, 2, 3$ where at each subband a new set of neighbors is chosen and a new linear predictor estimated.

3. Dimension Reduction and Visualization

Having extracted feature vectors for each sub-block of each of the ten images, the next question is, "do these clouds of points in 72-dimensional space actually serve as good descriptors of the image?" In this context, "good" must mean that points that come from the work of a single artist - and most likely, within a fixed genre as well - are nearby one another, yet simultaneously separated from a different artist's work in the same genre.

Standard approaches to this type of problem follow various methods of *dimension reduction* in which the high-dimensional feature vectors are transformed into 1,2, or 3-dimensional "approximations" that retain as much of the interpoint distances as is possible. Having reduced the data to a collection of points in a visualizable space, the reduced points are investigated for their clustering, or lack thereof.

In order to accomplish this we first computed the *Hausdorff distance* [5] between all pairs of images. The resulting 10×10 distance matrix (i.e., a matrix D such that D_{ij} is the distance between images i and j) was then subjected to a *multidimensional scaling* (MDS) [2] to arrive at the three-dimensional visualization shown in

[2]Integer rounding is used when computing the spatial positions of a parent, e.g., $x/2$ or $x/4$.

[3]To be precise, what we see here is the magnitudes of the reconstruction using the predicted subband coefficients coupled with the phases ($+1$ or -1) from the actual coefficients.

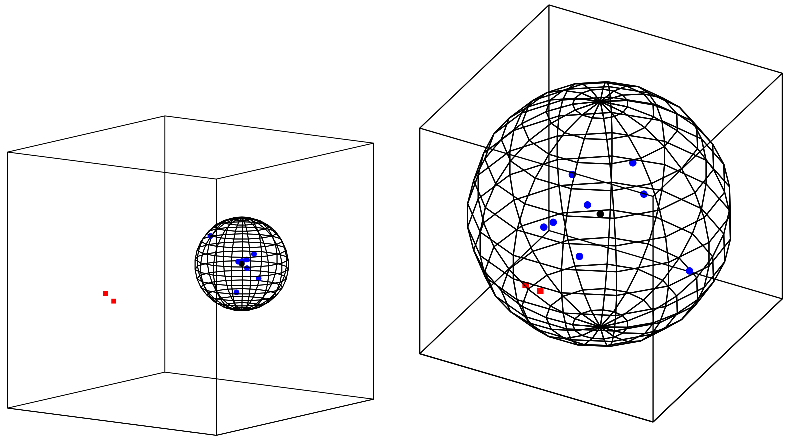

Figure 4: Application of data reduction and MDS separately to the sets of marginal statistics (left) and the error statistics (right). The error statistics still achieve separation while the marginal statistics do not.

Figure 3. Recall that given an $N \times N$ distance matrix D, MDS outputs a set of N points in some pre-specified dimension whose interpoint distances are as close as possible to those in D. Note that the points corresponding to the authenticated Bruegels cluster well away from the two imitations. In fact the difference of the means of the distances to the center of the sphere of the secture Bruegels and the imitations is statistically significant. Even in this reduced dimensional space, there is a clear difference between the authentic drawings and the forgeries.

Figure 4 shows the results of applying the dimension reduction procedure separately to the marginal and error statistic components of the feature vectors. That is, for each of the sets of 36-dimensional vectors of marginal statistics and error statistics we build separate distance matrices (using Hausdorff distance) and apply MDS for a three-dimensional visualization. Notice that after this process the marginal statistics no longer appear to separate the drawings while the error statistics do still succeed in achieving good separation.

4. Discussion

We have presented a computational tool for digitally authenticating or classifying works of art. This technique looks for consistencies or inconsistencies in the first- and higher-order wavelet statistics collected from drawings or paintings (or portions thereof). We showed preliminary results from our analysis of ten drawings either by, or in the style of, Pieter Bruegel the Elder. We expect these techniques, in collaboration with existing physical authentication, to play an important role in the field of art forensics.

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