Computer Analysis Reveals Similarities between the Artistic Styles of Van Gogh and Pollock

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Abstract

Recent advances in computer vision and image processing have enabled basic automatic analysis of visual art. Here we use computer analysis to extract thousands of numerical low-level image content descriptors from digitized paintings, and use them to objectively compare the similarities between the artistic styles of different painters. The analysis reveals that Vincent Van Gogh and Jackson Pollock share artistic styles that are far more similar to each other in terms of low-level image features compared to the similarity between the work of Pollock and other painters. The method proposed in this report can also be used to quantify similarities between painters or artistic styles based on large sets of numerical image content descriptors and detect influential links that might not be easily detected by the unaided eye.

Introduction

The analysis of art is a highly complex cognitive task that is not yet fully understood, as the different elements of visual art such as colors, shapes, and boundaries are processed by different pathways and systems in the brain designed to interpret each aspect of the art [1]. That is, in the absence of a central mechanism that receives and interprets visual art, pieces of information received from a painting are selectively redistributed to more specialized centers for processing. Observations using fMRI showed that experienced painter uses her brain in a different way than the non-painter, and EEG signal analysis also showed functional and topographical differences between artists and non-artists when performing visual perception of paintings, leading to the contention that artists perceive visual art in a different cognitive manner compared to non-artists [2][3].

The intensive and distributed brain activity supports the contention that the perception of visual art is not just about what the eye can see, but mainly about what the brain can process, so that painters can be classified in respect to how they probe the visual system with pictures [4][5][6]. Therefore, it has been stated that the painter does not paint with her eyes, but with her brain [7]. This approach suggests that the perception of art is driven by the perceptual processes that it activates in the brain of the viewer, rather than the identification of its aesthetic properties, and that artists use some form of over-stimulating distortion of reality and link it to the peak-shift effect [8].

While visual art is highly difficult to analyze manually in a quantitative fashion due to the complexity of the content, computers can provide an objective analysis that can be used to quantify similarities between paintings and artistic styles using various measurements of the image. The ability of computers to analyze visual art has been demonstrated by numerous algorithms and methods. For instance, computer algorithms were used to show that computers can associate impressionist paintings to their creating artists with accuracy higher than random [9]. Also, Multiresolution Hidden Markov Models and Wavelets were used to train a computer program to automatically classify Chinese ink paintings by the artists [10]. Additional work on computer-aided classification of paintings includes the identification of the painter by automatic analysis of skin samples, and classification of paintings based on repetitive features in the images [11][12]. Related works include automatic identification of drawing tools that were used by the artist, and computer-based methods of associating captions with paintings [13][14]. It has also been shown that a computer program can automatically associate different painters by their schools of art based on sample paintings from each painter [15]. While these methods were based on classification, the ability of computers to quantify similarities in visual art was demonstrated by the fractal analysis of the work of Jackson Pollock, which showed that Pollock's work features fractals, and that the fractality of his work changed across time [16][17][18][19].

Here we apply computer analysis and use several thousands low-level numerical image content descriptors that reflect different aspects of the visual content to paintings of Jackson Pollock and Vincent Van Gogh, and show that the artistic style of Jackson Pollock is significantly more similar to the artistic style of Van Gogh compared to the styles of other painters in terms of low-level image content descriptors.

Image dataset

The dataset used in this study is a set of 513 images of nine different painters, such that each painter was represented by 57 paintings [20]. The painters included in the dataset are Van Gogh, Monet, Pollock, Kandinsky, Rothko, Dali, Ernst, and deChirico.

The images were downloaded from various sources via the internet. While the numerous different sources that were used can increase the variance between the images, the fact that not all images come from the same source minimizes the source-dependency of the dataset, and verifies that the images are analyzed and characterized based on the actual image content and artistic style, rather than the source from which the image was acquired or artifacts in the image acquisition process [21]. For instance, if all Van Gogh images were acquired from one source while all Pollock's paintings were downloaded from another, a computer analysis might differentiate between the images based on the source, and not based on the content of the paintings or the artistic styles.

Since many different sources were used, the image sizes varied between 2458x1812 to 640x640 pixels. Normalization of the images was performed by first downsampling each image such that the shortest side was set to 600 pixels, and then cropping a 600x600 block from the center of the resulting image. This policy led to the sacrifice of some of the image area, but provided an image dataset of normalized size without changing the aspect ratio of the images [22]. Since the image size varies, the normalization ensures that the measured differences between the images will be driven by the visual content, rather than the different image sizes.

Image analysis method

The image analysis method used in this study is the *wndchrm* algorithm [23], which is based on a large set of different numerical image content descriptors that reflect the visual content of the image. These include high-contrast features such as edge and shape statistics, textures (e.g., Haralick, Tamura), statistical distribution of the pixel values (e.g., multi-scale histogram, first four moments), polynomial decomposition of the image, and fractal features. The features are extracted not just from the original image, but also from transforms of the images and transforms of transforms [24]. The transforms are the Fourier transform, Chebyshev transform, Wavelet transform (Symlet 5, level 1), edge magnitude transform, and Color transform [25]. Extraction of the image features from the original image and from the combinations of image transforms results in a large set of 4027 numerical image content descriptors [26]. This set of image features has shown its ability to reflect many aspects of the visual content, and previous experiments showed that the *wndchrm* method was capable of analyzing visual art by automatically associating paintings to their creating artists and artistic styles, as well as finding and measuring similarities between artistic styles of painters in an unsupervised manner [27][28].

While the purpose of the large set of image content descriptors is to reflect as many different aspects of the visual content as possible, many of these features are expected to be uninformative for a certain given image dataset, and might therefore represent noise. For instance, by using color features alone the analysis might show that Rothko's *Untitled 1969* is similar to the work of Pablo Picasso's blue era, while other features, such as edges or polynomial decomposition coefficients, can provide quantitative information that differentiates between the two different styles. Therefore, color features might not be considered informative in that specific dataset, while polynomial decomposition and edge features provide useful information that discriminates between the two artistic styles.

To reduce the effect of uninformative image features, each feature is assigned with a Fisher score that represents its informativness for discriminating between the classes in the specific dataset at hand [29]. When a feature vector of a test image is classified, a simple Weighted Nearest Neighbor rule is applied such that the Fisher scores are used as the feature weights. This classification method allows the use of a large number of image content descriptor that work in concert, and provides analysis that is based on a broad range of visual aspects [30]. Another advantage of this classification method is that the weighted distance measured between the feature vectors allows assessing the similarity between each pair of images in the dataset [31]. The source code and executables of *wndchrm* are publicly available at http://vfacstaff.ltu.edu/lshamir/downloads/ImageClassifier.

Results

The similarities between the artistic styles were compared by using the Weighted Euclidean Distance between the vectors of numerical image content descriptors, such that the weights were the Fisher scores of the painters [32]. That is, the similarity between each two paintings in the image dataset was measured by the weighted Euclidean distance between the values of the image content descriptors of each painting. The distances between the pairs of paintings can be visualized using an evolutionary tree by applying the phylip software package [33]. This visualization showed that Van Gogh and Pollock paintings were clustered together, indicating that the paintings of these two painters are more similar to each other compared to other pairs of painters [34].

The measured similarities between the paintings or artistic styles can be biased by a few image content descriptors that highly correlate across painters. For instance, if a certain pair of painters tends to use similar colors, the color features for both painters will have similar values. This can bias the similarity measured between the paintings of the two artists, and might lead to a conclusion that they share a similar artistic style, even if the only thing they have in common is the colors that they use, which is merely a weak indication of a direct influential link. Therefore, to test for artistic similarities between painters, it is required to consider many image content descriptors that measure different aspects of the paintings, and can together indicate on artistic similarities.

To compare the similarities between the artistic styles of the painters as measured using the computer analysis, we compute the mean of the values of each feature extracted from all paintings of each artist. Then, the means are compared in order to test which pairs of artists are the most similar in the context of that specific image feature. For instance, if the mean value of the Tamura texture directionality computed from all images of painter A is 0.5, and for the images of painter B the mean is 0.6, while the mean of Tamura texture directionality computed from the images of painter C is 0.8, it can be said that painter A is more similar to painter B than to painter C in terms of Tamura texture directionality. Repeating this using a set of over four thousands different image features that have been shown to be informative for computer analysis of art can provide an estimation of the similarities between the artistic styles of different painters, as reflected by low-level image content descriptors [35].

Since a very large set of image features is used, many of the image features are not expected to be informative for identifying similarities between artistic styles, and therefore represent noise. In order the weight the image features based on their ability to assess the differences between artistic styles of painters, each image feature is assigned with a Fisher score that is determined based on the values of each numerical image feature extracted from paintings of the different painter classes [36]. The Fisher scores therefore weight and rank the features by their ability to differentiate between the painters.

To study the similarity between the artistic styles of Van Gogh and Pollock, we computed the image features for 57 of Pollock's paintings, as well as 57 paintings of Van Gogh, Monet, and Renoir. Then, the Fisher scores were computed based on the ability of each feature to differentiate between the artistic styles of the painters. The comparison to the work of Claude Monet was due to the influential link between Monet and Van Gogh and the similar painting methods, as both painters used short brushstrokes with dots and swirls. Renoir's work was selected because it was created at around the same time and the same country as Van Gogh's work, and both painters were influenced by the same artists and artistic styles. At the absence of known direct influential links between Pollock and a specific painter in this group, their artistic styles are expected to be equally similar to the style of Jackson Pollock.

Figure 1 shows the amount of the ranked-ordered image features computed from the paintings of each of the three painters that their means are the closest to the mean values of the same features computed from Pollock paintings. That is, if the mean values of a certain image feature are 0.5, 0.6, and 0.7, for Van Gogh, Monet, and Renoir, respectively, and the mean value of the same feature across Pollock's painting is 0.4, then it can be said that the most similar artist to Pollock in terms of that feature is Van Gogh. The features are ordered by their informativeness, based on the Fisher scores.

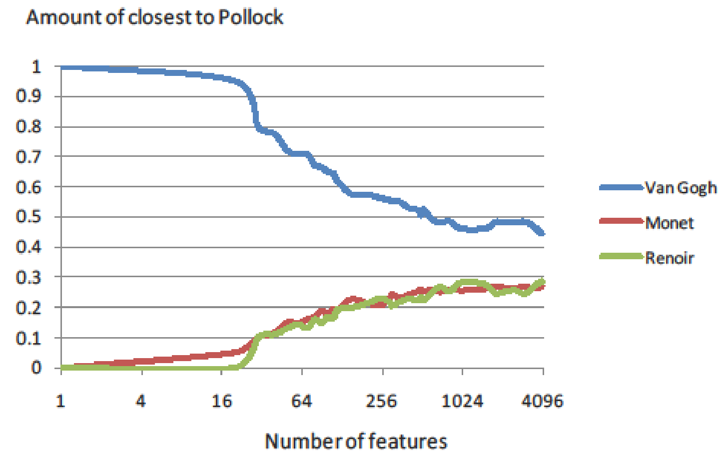

Figure 1. The amount of ranked-order image features that are the closest to the mean feature values extracted from Jackson Pollock's paintings.

As the figure shows, the values of most of the informative image features show high similarities between the means of the values computed from the paintings of Van Gogh and the mean feature values computed from the paintings of Pollock. For instance, among the 20 most informative image features 19 have mean values that are the most similar to Van Gogh, and 57 of the top 80 image features. If the means of the image feature values were randomly distributed, the probabilities that 19 of the 20 most informative features and 57 of the top ranked 80 features are most similar to one of the painters is ~$5.4*10^{-12}$, and ~$1.2*10^{-11}$, respectively. Also, the Pearson correlation between the mean values computed from Van Gogh and Pollock for the 80 most informative image features is 0.71, which is significantly higher than the correlation of the features computed from Pollock's paintings to Monet and Renoir's paintings, which are 0.405 and 0.352, respectively. This shows a higher similarity in terms of low-level image content descriptors between the artistic styles of Van Gogh and Pollock, compared to the similarity of Pollock's paintings to the styles of Renoir and Monet.

The similarity between Van Gogh and Pollock's paintings can also be evident by the ability of an image classifier to differentiate between the two artists based on analysis of low-level image features. That was done by training three binary image classifiers with 40 images from each painter, and testing each classifier with 17 paintings per painter. The binary classifiers were trained to automatically differentiate between paintings of Pollock and Van Gogh, Pollock and Monet, and Pollock and Renoir [37]. Each classifier was tested 50 times such that in each run the images were randomly allocated for training and test sets. The automatic classification between the paintings of Van Gogh and Pollock using low-level image content descriptors was accurate in just 92% of the cases, while the accuracy of the two-way classifiers between Pollock and Monet or Pollock and Renoir was 100% in both cases [38]. The classification accuracy was also perfect when classifying Pollock and other painters such as Dali, Ernst, de Chirico, Kandinsky and Rothko, showing that the style of Pollock as measured by low-level image features was more similar to Van Gogh than to abstract expressionist painters such as Rothko and Kandinsky [39].

The similarity between the artistic styles of Van Gogh and Pollock in the sense of low-level image features is reflected also by the Fisher scores of the image content descriptors that discriminate between them. When classifying the paintings of Van Gogh and Pollock using the *Wndchrm* algorithm, the image feature that provided the strongest discriminative power (Fourier Wavelet Fractal 0 in the *Wndchrm* scheme) had a score of 0.77, and the mean score of the 100 most discriminative features was ~0.62. These scores are lower than the scores of the most discriminative features used for Monet/Pollock and Renoir/Pollock classifications, which were ~1.34 (Multiscale Histogram of the Color Transform), and ~1.32 (Zernike of Edge Fourier Transform), and the mean scores of the 100 most discriminative features were ~0.81 and ~0.83, respectively. Again, these values show a significantly higher similarity of the paintings of Van Gogh to the paintings of Pollock compared to other painters, and indicate on influential links that can be sensed in low-level image content descriptors.

Since visual art is highly complex, measuring similarities between artistic styles should be based on different aspects of the visual content, and show that the similarities between the styles is reflected by very many different image features. Figure 2 shows the informativeness of the different image content descriptors for the classification between the set of Pollock's paintings to the paintings of Van Gogh, Monet, and Renoir, such that the values are the sums of the Fisher scores of all bins of the different feature groups extracted from the different image transforms. For instance, if the Tamura texture features used in the analysis have six different numerical values, the informativeness of the Tamura textures is measured by the sum of the six values.

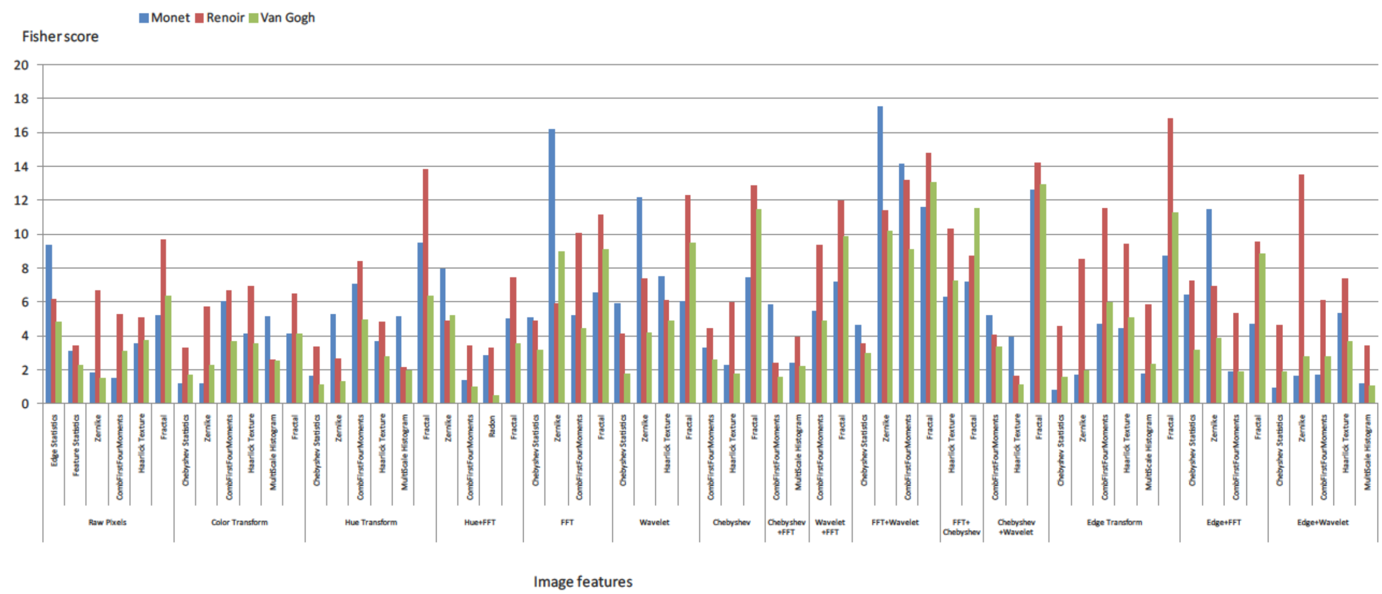

Figure 2. Fisher scores of the image features computed on the different image transforms and compound image transforms. The graph shows features that their Fisher scores for at least one of the three painters are greater than 3.

As the figure shows, most low-level image features provide stronger classification signal between the paintings of Pollock and Monet or Pollock and Renoir, compared to discrimination between Pollock's and Van Gogh's paintings. Another thing that is noticeable from the figure is that image features extracted from the transforms and compound transforms can be more informative than image features extracted from the raw pixels. This observation, however, is not surprising, as it has been shown that in many cases image features extracted from transforms can provide stronger classification signal compared to image features extracted from the raw pixels [40].

While most low-level features show higher similarity between Pollock and Van Gogh, a noticeable exception is the fractal features that are used by *wndchrm* [41][42]. The fractal features clearly discriminate between Monet and Pollock as well as Renoir and Pollock, but unlike most other low-level image features, the informativeness of the fractal features is not stronger when classifying Van Gogh and Pollock paintings. However, compared to the other low-level image features that are used to discriminate between Van Gogh and Pollock, the presence of the fractal features among the most discriminative image content descriptors is far stronger compared to Monet or Renoir. Figure 3 shows the amount of fractal features among the most informative image features that discriminate between Pollock and Van Gogh, Monet, and Renoir.

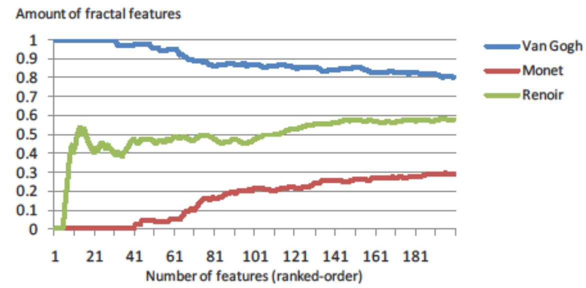

Figure 3. Amount of fractal features among the most informative 200 features that discriminate between paintings of Pollock and Van Gogh, Monet, and Renoir.

The unique fractality featured in Jackson Pollock paintings is expected to provide a source for classification signal between Pollock's paintings and the work of other painters [43]. As the figure shows, the presence of the fractal features for discriminating between Pollock's and Van Gogh's paintings is far stronger compared to the paintings of Renoir and Monet. For instance, among the 60 most informative low-level image features that discriminate between Pollock and Van Gogh merely three are not fractal features. However, when looking at the absolute Fisher scores, the absolute scores of the fractal features that discriminate between the paintings of Van Gogh and Pollock are actually smaller than the Fisher scores of the fractal features that discriminate between Pollock and Monet or Renoir. For instance, the highest Fisher score of a fractal feature that discriminate between Pollock and Van Gogh is ~0.77, and the sum of the highest 20 Fisher scores of fractal features is ~0.68. These numbers are not significantly higher than the highest Fisher scores of fractal features that classify between Pollock and Renoir and Pollock and Monet, which are ~0.96 and ~0.72, respectively, and the sum of the 20 highest scores of the fractals features used in these classifiers are ~0.68 for the classification between Pollock and Monet, and ~0.86 for the Pollock/Renoir classifier.

This shows that the fractal differences between Van Gogh and Pollock do not provide stronger discrimination signal compared to the discriminative power of these features for Pollock/Monet or Pollock/Renoir classification, and that the similarity reflected by the low-level image features between Van Gogh and Pollock is not driven by fractality. However, since the other low-level features are weaker, the fractal features provide most of the signal for the automatic classification between Van Gogh's and Pollock's paintings. This shows that while the artistic styles of Jackson Pollock and Van Gogh might be more similar in terms of low-level image content descriptors, the similarity between the styles is not reflected by the fractality of their work, and the unique fractality in the work of Jackson Pollock does not seem to be present in the paintings of Van Gogh.

Since the fractal features are so dominant for the classification between Van Gogh's and Pollock's paintings, eliminating the fractal features sharply reduces the accuracy of the automatic classification between Van Gogh and Pollock paintings, compared to Monet and Renoir. Without the fractal features the classification accuracy between Van Gogh and Pollock was 83%, while eliminating these features did not affect the classification accuracy between Pollock and Monet or Pollock and Renoir. This shows that while the fractal features are generally not more informative for classification of Van Gogh and Pollock paintings compared to the other painters, their absence affects the performance of the classifier due to the absence of other low-level features that can effectively classify between the two painters.

Discussion

It has been shown in the past that characteristics of aesthetics can be measured, and that statistics of scene-centered primitives correlate with the human perception of aesthetics [44][45]. These primitives can also be used to evaluate the structure of a scene image [46]. Here we showed that analysis of measureable image content descriptors indicates that the artistic style of Vincent Van Gogh is more similar to that of Jackson Pollock compared to other painters. This analysis is based on more than four thousand numerical low-level image content descriptors that work in concert and reflect many different aspects of the visual content of the paintings.

While the human eye can in many cases discriminate between artistic styles, computer-based low-level image features reflect a combination of very many aspects of the image that are not necessarily noticed by the unaided eye or perceived by the human brain. Therefore, using large sets of low-level numerical image content descriptors can reveal information about the differences between different paintings, artists, and artistic styles, which are difficult to sense by manually observing the images. Another important advantage of the computer analysis is that it provides an objective analysis that can be used to quantitatively measure the differences between artists and artistic styles, a task that is practically impossible to perform by manually observing the art.

The work described in this report shows that computer analysis can be used to find similarities and influential links between different artists and works of art in a systematic and objective manner that is not limited or biased by the perception of the human eye, and can therefore detect patterns of similarities that might not be easy to detect or measure by the unaided eye. Future work will focus on detecting similarities suggesting influential links between individual paintings, as well as systematic search for similarities reflected by numerical image content descriptors in larger networks of painters. These larger networks will potentially allow detecting more possible influential links between artists. The full source code used for this study is available for free download at http://vfacstaff.ltu.edu/lshamir/downloads/ImageClassifier , and can be compiled to a command line utility.

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