Chapter 22

COMPUTERIZED ANALYSIS OF PAINTINGS

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> Nature is not only all that is visible to the eye... it also includes the inner pictures of the soul.
>
> Edvard Munch (1863-1944)

Abstract

As hundreds of thousands of paintings, including many of the most significant historical works, have been digitized in high resolution and made available to the public, scientists have started to utilize some of the latest image analysis and artificial intelligence tools to study these paintings. Such computerized analyses can provide valuable insights to art historians regarding attribution, dating, cataloging, and comparative analysis, and recent advancements in computerized analysis of artistic paintings have branched out to employ novel approaches and to do so for various purposes. For example, computerized analysis based on statistical learning and modeling has the potential to predict emotions evoked from visual arts. In a similar vein, interest in art may be increased by automated personalization of art experiences in museums and on the Web. Moreover, the analysis of a large volume of historical paintings may shed light on important topics such as aesthetics, composition, and emotions. Finally, we present our vision for the future of the field, including the anticipated impact of painting analysis to the development of artificial intelligence.

Introduction

With advancements in imaging technologies, the efforts to digitize fine art paintings have increased dramatically since the turn of the century. These efforts have made hundreds of thousands of paintings digitally available. This unprecedented access enables researchers to analyze computationally a large number of paintings concurrently and in a way that was previously impossible. The analysis tasks, such as stylometry, attribution, authentication, dating, and comparative study, which used to be done on a small number of artworks by art historians and connoisseurs, can now be conducted over a large digital collection of artworks using automated methods.

Traditionally, art historians have employed a range of tools to analyze paintings.[1] In particular, to scrutinize materials that artists used in the paintings, art historians have exploited raking light photography, ultraviolet fluorescence illumination, infrared imaging, cross-section paint and varnish analysis, microscopic analysis, chemical composition analysis, X-ray imaging, multi-spectral imaging, laser 3D scans, and synchrotron induced X-ray fluorescence mapping. Connoisseurs often have in-depth knowledge about an artist's distinctive way of painting, his or her "signature brushstroke style," and unique techniques. Art historians also comb artists' letters, diaries, notes, and other written materials in their analyses, especially for the purpose of verifying the authenticity of paintings.

The computerized analysis of paintings cannot replace conventional methods used by art historians, but it does provide three benefits. First, it is in general non-invasive. Computerized analysis is usually conducted on digital images of paintings, and thus, no additional damage happens to the painting beyond what may be caused by the imaging technique itself. Secondly, computerized analysis provides information not available from other techniques. With the advancements of modern computer vision and image analysis, one can analyze the artist's style used in a painting through the statistics gathered from thousands of extracted brushstrokes, lines, curves, angles, and/or color patches. Modern computer graphics methods can also provide information on the accuracy of the artist's depiction of the three-dimensional world and the lighting environment. Thirdly, computers can analyze and discover useful findings from a virtually unlimited number of paintings. This advantage allows art historians and scientists to build models of artistic styles from collections of paintings of a particular period of an artist, the lifetime of an artist, an artist's school, an art movement, a painting genre, and so on. Since the early 2000s, we have undertaken computerized analyses of paintings from different cultures, ranging from Chinese ink paintings to Post-Impressionist oil paintings.[2] In this chapter, we will share some of our experience, discuss related work by other scientists, and propose possible future directions.

Stylistic analysis requires knowledge of composition principles and techniques employed in different art movements or by artists in various time periods. The disparities and commonalities between styles or art movements are intricate, making it impractical for a single expert or a small group to master even a significant portion of the facts and relationships about all styles or movements. Furthermore, stylistic analysis demands an immense amount of time as it is necessary to go through each painting meticulously and to compare the details with other paintings in a large collection. Art historians, artists, and curators must devote many hours to this task, which can be prohibitive for often insufficiently funded artistic establishments. As a result, existing studies focusing on stylistic comparison are limited in scope. Efforts to automate this long and resource-consuming process have arisen in computer vision analysis. Computerized style analysis enables the automation of several relevant tasks, including cataloging and chronological sorting. When styles can be automatically distinguished and categorized, the once tedious work of cataloging an extensive collection of paintings becomes manageable. Matching styles with different eras or different periods in a painter's life is another important inquiry for art historians and curators that can be assisted tremendously by computerized analysis.

The authentication of artworks is another pursuit of art historians that demands expert knowledge and an enormous amount of time, but it is open to computerized analysis to a certain extent. The computational approaches, if carried out properly, can be advantageous. For instance, with the help of unlimited computing power, authentication can be determined from information and statistics based on high-confidence attributions from hundreds or even thousands of paintings, making the process evidence-based and substantially more objective. Furthermore, modern imaging modalities may reveal properties inherent to a specific painting that are invisible to the naked eye and difficult for humans to evaluate due to their high dimensionality or other properties. Computer algorithms (i.e. processes computers take in solving problems) can be developed to take advantage of the large quantity of available visual data. A new field of science – data science – is advancing rapidly to use computing and statistics for extracting useful knowledge or insight from data. Computerized comparative methods can be leveraged to compare and authenticate various paintings in a time efficient manner. Similar methods can be utilized to obtain information about unattributed paintings that were found many years after they were painted.

Data-driven methods, however, are not applicable in every situation. Because such methods often rely on high-quality manually annotated data for training (a process to "teach" computers about various concepts), application is limited by the availability of data. For example, determining whether a particular painting is a forgery through data-driven methods would require exposing the computer program to a representative collection of counterfeit paintings for the relevant artist. This requirement is often difficult to satisfy because it is impossible to procure a large and representative collection of counterfeits. While comparisons can be made directly to known genuine works of a painter to assess proximity to the painter's style, such methods are not always dependable. For instance, it is possible that the stylistic differences between the genuine works and some counterfeits are not captured in the computed features used for the comparison. This can lead to false acceptance of counterfeits as genuine works. Also, some genuine works of a painter whose styles are divergent may deviate from the set of known genuine works with which the paintings are compared with, and that can lead to false alarms.

Computerized analysis, despite the above limitation, allows for novel research on how humans interact with art. With recent technological advances in affective computing and personalization, for example, researchers have begun to develop algorithms to predict the emotions elicited by paintings and their properties such as style, color, and composition. This information can be leveraged for encouraging particular audience responses to an exhibition (whether physical or online) and personalize such experience. Research in this area often makes use of psychological theories of emotions and human-generated emotion data, which creates certain curatorial and analytical challenges. Emotion is highly subjective, making its modeling extremely difficult even in the case of naturalistic photographic images. To model the emotions generated by paintings, particularly those that are abstract in nature, an additional challenge is the absence of high-quality, human-generated emotion data derived from responses to such works.

In the remainder of this chapter, we introduce recent computational advancements in analyzing paintings. We first provide information on datasets used in computational painting analysis studies and then explain how the tasks mentioned above benefit from computerized methods.

Datasets for Analyses

Computerized painting analysis relies on equipping computers with detailed information about historical artistic concepts and styles – a process that is often referred to as "training." This process demands high-quality image datasets and manually generated annotations. The selection of the paintings for a dataset needs to be appropriate for the goals of the particular study. This typically requires the dataset to be large enough, sufficiently representative, and of high digitization quality to cover pertinent details and nuances.

The proper digitization of color paintings involves significant technologies and skills. The lighting conditions, camera quality and settings, digitization process, and the color space (in this context, a mathematical model to describe colors in the physical world using numerical values) and the digital image format used to store the images can all affect the fidelity and usefulness of the resulting images. For example, if the color balance is not based on a standard color calibration chart, the resulting images can suffer a color shift that is impossible to eliminate completely at the stage of computational analysis. Similarly, different digitization processes can also introduce various technical artifacts (sometimes referred to as "noise") that can steer some machine learning methods to focus on the noise profiles rather than on the actual useful information from the image data. To manage issues of image quality for conventional imaging methods, we have developed shape- and texture-based methods that are less affected by the problems with color accuracy or digitization quality.[3]

Lumiere Technology, a company based in France, has been digitizing some of the world's best known paintings, including Leonardo da Vinci's *Mona Lisa*, using specialized multi-spectral imaging equipment.[4] As such high-quality image data becomes available, researchers can analyze paintings with accurate colors ranging from ultraviolet to infrared that extend well beyond ordinary human perception.

Existing computational studies utilize small to medium range datasets with varying digitization quality for method validation (a principled process to justify the performance of a proposed method on data that was kept apart during training). These can be grouped into three categories: artistic style, artist, and genre.[5]

- **Artistic Style Datasets.** In one study, the dataset comprised 513 paintings by nine different painters (Claude Monet, Jackson Pollock, Vincent van Gogh, Pierre-Auguste Renoir, Wassily Kandinsky, Mark Rothko, Salvador Dalì, Max Ernst, and Giorgio de Chirico).[6] A different study included local annotations such as poses and style labels for 988 monochromatic paintings acquired from the Artstor digital art library.[7] Khan et al. introduced a dataset of 4,266 paintings from 91 artists that provides artist and style annotations along with eye-tracking information. Another study in style identification involved two large datasets, with one containing approximately 50,000 images obtained from community-curated Flickr groups[8] and the other containing about 100,000 images procured from WikiPaintings (WikiArt). A study that investigated children's book illustration styles included 6,468 illustrations by 24 different illustrators.[9]

- **Artist Datasets.** Johnson et al. worked with museums to create a dataset of 101 high-resolution scans for the purpose of analyzing and dating Van Gogh's paintings.[10] Among the 101 paintings, 82 were consistently attributed to Van Gogh, 6 were identified as not being by Van Gogh, and 13 had been or were at the time questioned. Another dataset was introduced by Elgammal, Kang, and Leeuw that contains 297 authentic drawings attributed to Pablo Picasso, Henri Matisse, Egon Schiele, and Amedeo Modigliani among others, as well as 83 forged drawings by those artists.[11] In a visual recognition challenge in 2014, a fairly large dataset was created that contained 112,039 high-quality artwork images from 6,629 artists with 1,824 art types (e.g., print making, painting) along with material and date labels.[12] In addition, the dataset provides annotations for the year of and materials used for creating the artwork.

- **Genre Datasets.** While genre classification is, in general, not of interest to art historians, it poses a challenging problem to artificial intelligence (AI) researchers. Different from conventional photo classification problems, the expressive or abstract nature of artistic paintings makes their computerized classification more difficult. Siddiquie, Vitaladevuni, and Davis created a dataset that included 498 paintings derived from six genres: Abstract Expressionism, Baroque painting, Cubism, Graffiti, Impressionism, and Renaissance art.[13] In another genre classification study, a dataset comprising 353 images was produced from works associated with Abstract Expressionism, Cubism, Impressionism, Pop art, and Realism.[14] Recent studies are producing larger datasets. Agarwal et al. presented a dataset containing 1,800 images from six genres (300 images for each genre).[15] Florea, Toca, and Gieseke introduced a dataset of 18,040 paintings from eighteen genres, with balanced numbers of images in each genre.

The increase in dataset number and size signifies the importance and interest paid to the computerized analysis of paintings in technical communities. Along the same lines, the diversity in datasets contributes to the ability of computer-based approaches to take on different tasks in this domain. Having different datasets available inspires art historians and computer and information scientists to formulate new challenges. We hope that, over time, more integrated datasets with high quality digitization methodology and comprehensive metadata descriptions of the works can be available.

Stylistic Analysis

An interest in automating stylistic analysis has developed in the computer vision community, leading to a number of different approaches. Existing approaches fall roughly into two groups: "feature engineering-based methods" and "feature learning-based methods."

In **feature engineering,** visual features are first designed and programmed by computer scientists. The programs are applied to images of paintings to extract numerical features, which are taken as input for a statistical classification algorithm. Such methods leverage the skills, experience, and intuition of experts who are required to identify salient and computable features of the works. In the early 2000s, Li and Wang pioneered this method for analysis in their study of classic Chinese ink paintings.[16] Performance of such methods depends on the relevance of the selected features to the style of the work and the effectiveness of the classification algorithms.

Painting styles pertain to identifiable statistical characteristics such as wavelet features and edge orientation.[17] Most of the features extracted across studies involve a focus on edge properties, texture, and color.[18] Other examples include active shape models for face detection and MPEG-7 description features (MPEG-7 is a multimedia content description standard which makes the search of multimedia content easier. The standard includes encoded information about the color and texture of the content.)[19]

The work of Li and Wang models local features constructed from wavelet coefficients by spatial stochastic processes (*i.e.* mathematical models that capture random behavior of a system over time or space), in particular, the multiresolution 2D (*i.e.* spatial) hidden Markov models. The computational process essentially characterizes different types of brushstrokes in Chinese ink paintings, *e.g.* swift and thin strokes on relatively smooth backgrounds, flat controlled strokes, heavy and thick wash, straight and pale wash with some vertical lines, small dark strokes, sharp lines and straight washes, and pale and diluted wash. Figure 22.1 shows an example patch of each of these brushstroke types as detected by the computer program.[20]

A more recent work by Vieira et al. leveraged shape, texture-complexity, and curvature features for stylometry (i.e. a set of principled approaches in art to understand and quantify the visual style of an artist). After an initial image segmentation, shape measures, *e.g.*, perimeter (contour length of segments), area (number of pixels for each segment), convex hull area and its ratio to original segment area, and circularity (ratio of perimeter and area of each segment) are computed. To characterize texture, entropy (i.e. a mathematical measure of the amount of changes within an image region) and Haralick features (i.e. visual features computed through co-occurrence of similar tonal values within sub-regions of an image) were employed. Mean and standard deviation of edge curvatures were calculated, then high curvature points (peaks) and distance between peaks were added. Applying feature selection showed that the mean of curvature peaks and the average segment area were the most relevant for style classification. They created a "painting space" and style centroids for classification.[22]

Liu et al. applied multi-task dictionary learning to features extracted from paintings of six different styles: Baroque, Cubism, Impressionism, Postimpressionism, Renaissance, and Modern. This method

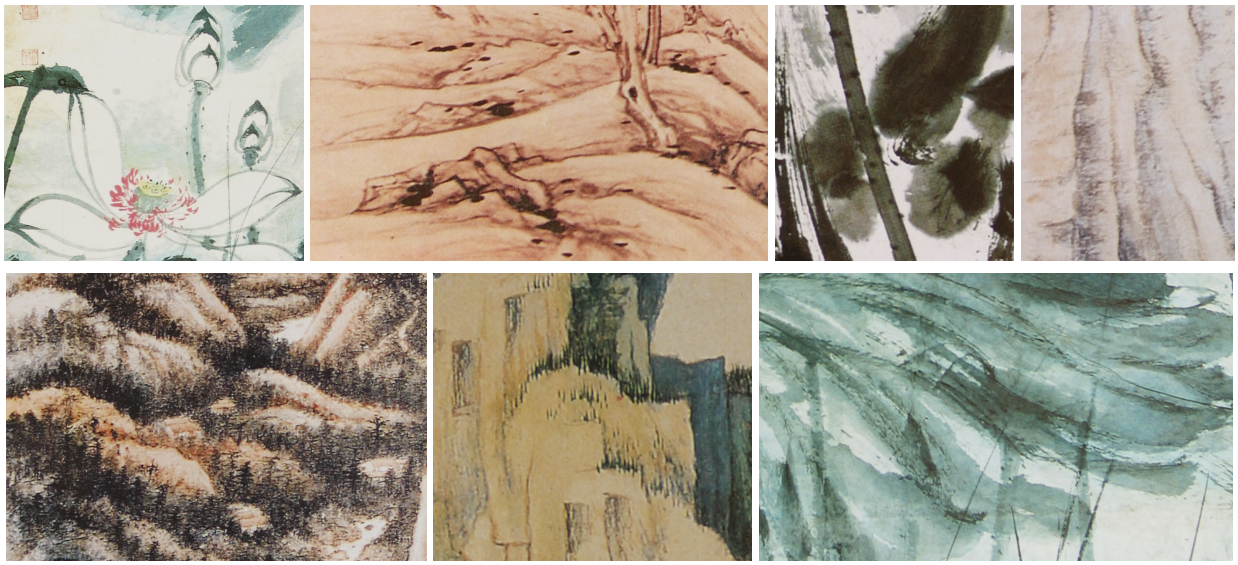

Figure 22.1: Different types of brushstrokes from classic Chinese ink paintings are automatically extracted from the paintings. The distributions of these brushstroke types are used to compare the styles of different artists[21]. These patches are from color ink paintings by Zhang Daqian (1899-1983), with color information not used in the analysis.

exploits color, composition, and line features. Global and local color features captured include the temperature of color, weight of color (darker/lighter shades), and expressiveness of color (contrasts in hue, saturation, and value channels). Composition quality measures were defined based on spatial saliency map distribution for the "rule of thirds," and symmetry and rectangularity in saliency for the "golden section principle." The means and standard deviations of the detected line slopes and lengths were computed. Using these features, the researchers created a dictionary to classify painting styles.[23] Another classification method uses scale-invariant feature transform (SIFT), gist features, histogram of gradients (HoG), local binary patterns (LBP), gray level co-occurrence matrix (GLCM), and Lab color distribution.[24] The extracted information is then fed into an ensemble of support vector machines (SVM) for classification.

Li, Ray, and Lindsay advanced a nonparametric statistical approach that can be used for dominant color detection[26]. This approach detects clusters by picking samples that approach the same frequent information (modes). This method can detect the dominant colors in a painting and provides color palette-like information which can be used to study style. Figure 22.2 shows the resulting dominant colors detected from paintings and the color's locations on the color wheel.

Another study benefits from discrete tonal and variational measures.[27] Tonal measure characterizes tonal variations within differently sized "visual neighborhoods" in an image. Variational measure represents the entropy within those "visual neighborhoods." The study shows that tonal distribution and variations in color and texture are important to quantify visual style. In a different study, MPEG-7 multimedia content description scheme was leveraged in art classification.[28] The content description includes features such as scalable color, color layout, color structure, dominant color, edge histogram, and homogeneous texture. The authors experimented with a dataset of 600 paintings of 18 artists from different movements and showed the usefulness of the feature for classification.

An interesting study of Byzantine religious iconography that does not explicitly depend on color,

Figure 22.2: Dominant colors used by the artist are revealed through a statistical computing method[25]. The paintings shown are *A Sunday Afternoon on the Island of La Grande Jatte* (and a portion enlarged) by Georges Seurat (1859-1891), Paris, 1884-1886, *Water Lilies* by Claude Monet (1840-1926), Giverny, 1919, and *The Fighting Temeraire* (and a portion enlarged) by J. M. W. Turner (1775-1851), 1838. Colors with higher saturation locate farther away from the center of the color wheel. The painting images courtesy of the Art Institute of Chicago and the Google Art Project, The Metropolitan Museum of Art (New York), and The National Gallery (London), respectively. The images showing the dominant colors courtesy of Jia Li.

texture, or orientation features has made use of facial landmark features.[29] The immense amount of time that has passed since the works were made presents challenges such as loss of paint and cracks in the icons themselves. The facial features of the subjects were computed following the selection of 44 "landmark points" on each face. In order to overcome the noise caused by the aforementioned reasons, independent component analysis (ICA) was applied to sieve out more robust image representations (second and third basis functions). Different shape models were utilized for different poses. This approach makes it possible to automate classification and analysis of the evolution of religious iconographs in a structured manner.

Feature learning makes use of statistical learning methods (*e.g.* artificial neural networks) to determine the relevant features useful for an analysis task instead of defining them in advance. While this approach is often faster in generating an effective classifier, machine-generated features commonly do not offer the ability to explain the reasoning behind the decisions made by the program in a way that art historians and art enthusiasts can interpret and use in their art historical analyses. Further, such methods are prone to biases introduced in the dataset and/or the modeling process.

The use of neural networks for feature learning eliminates the phase of handcrafting visual features that might be relevant for computerized painting analysis.[30] A sufficiently deep neural network, i.e., a network with multiple layers of artificial neurons, might extract the patterns that are common to certain group of paintings.[31] The different layers of the network become attuned to those patterns. These learned patterns can be fed into a classical classification framework.[32] Another approach that replaces designing visual features that may distinguish paintings involves a statistical approach.[33] An atomic visual library is created, which contains small image patches that frequently occur among similar paintings (called *"visual words"*). By learning the vocabulary, similar style paintings can be identified as they usually contain similar visual words. This approach can capture global and local properties of paintings. In a children books illustration study, Hicsonmez et al. demonstrated that performance of different deep-learning-based methods is better than traditional low-level feature-based methods in style classification.[34]

Furthermore, neural networks can be utilized in a generative way to understand the underlying structures of classes of paintings. This framework is composed of two neural networks (generative and discriminative) where the generative network tries to deceive the discriminative network. Through iterations, the former produces images close to training data samples. The analysis of this network can provide ideas about which features can be used to classify the paintings. A bi-product of such methods is the automatic generation of art-like images that imitate artists' creativity although this approach is limited and in its infancy.[35]

Attribution, Authentication, Dating, and Restoration

Artist identification, authentication, and dating of paintings are of great interest to art historians, curators, and collectors. Providing definitive answers to questions of attribution is often extremely challenging, even when using a combination of modern technologies. Different imaging modalities can inspect various aspects of paintings in more detail, while high-energy physics can detect underpaintings and the material makeup of the painting.

Our earlier work attempts to find characteristics that distinguish Van Gogh's works from those of his contemporaries, to identify works in different periods of Van Gogh's career, and to date certain of his paintings.[36] As shown in Figure 22.3, a computer program was able to extract brushstrokes from paintings automatically. On the basis of this data, we computed brushstroke statistics, based on individual brushstrokes, interactions between brushstrokes, and whole-painting statistics. The method offers the ability to explain to art historians the exact reasoning behind the conclusions. For example, the team was tasked to date three paintings that are attributed to Van Gogh: *Still Life: Potatoes in a Yellow Dish* (ID# F386), *Willows at Sunset* (F572), and *Crab on its Back* (F605). Their method produced explainable evidence, based on an analysis of thousands of brushstrokes and their interrelations, to date the paintings F386 and F605 to the Arles and Saint-Rémy period, and the painting F572 to the Paris period. Further, the method has statistically revealed the marking attributes of Van Gogh's brushstroke style: density, elongatedness, straightness, and homogeneity.

Figure 22.3: Brushstrokes are automatically extracted from the painting *Red Cabbages and Onions*, Vincent van Gogh (1853 - 1890), Paris, October-November 1887[37]. The painting image courtesy of the Van Gogh Museum, Amsterdam (Vincent van Gogh Foundation). The brushstroke image courtesy of the James Z. Wang Research Group (The Pennsylvania State University).

Various other researchers have devised different methods to detect or analyze specific painters. They have studied Vincent van Gogh,[38] Pieter Bruegel the Elder,[39] Jackson Pollock,[40] and Piet Mondrian,[41] for instance. Studies have also been carried out to distinguish genuine works from imitations[42] or forgeries.[43]

Computerized analysis has been shown to be valuable to help answer anthropological and archaeological questions. Wang et al. used machine learning to study the roles of men and women in prehistoric contexts by analyzing the sexual identities of human handprints stenciled on the breathtaking wall panel of the Gua Tewet cave of eastern Borneo and around the *Leopard Spotted Horses* mural of the Pech-Merle cave in southern France.[44] The study provides quantitative evidence relevant to sexual dimorphism and the sexual division of labor in Upper Paleolithic societies.

In addition to automated direct attribution and authentication, image analysis can also assist with the physical analysis of paintings through cleaning the artifacts or restoring them for further analysis in different imaging modalities. For instance, Cornelis et al. determined how to remove canvas patterns that show up during the high resolution and X-ray imaging of paintings. The authors propose a two-stage approach. First, they decompose the image into two parts where the first part contains contrasted shapes (cartoon) and the second part consists of oscillating patterns (texture). The textural part contains the canvas patterns. Multiscale thresholding was then applied to the textural part in the frequency domain to filter out the canvas patterns.[45]

Image analysis is also employed to restore cracks or faded colors in paintings. A method for crack detection and inpainting was put forward by Cornelis et al. The method combined three approaches for crack detection, including the use of oriented-elongated filters, morphological operations, and sparse representation dictionaries. Each approach investigates a different quality of the cracks: sensitivity, width selectivity, and smoothness. The background and foreground of a detected crack were first delineated with a Markovian field segmentation. In this process, candidate patches of variable sizes were selected as targets, the cracks were filled and the image was restored.[46] Color fading due to chemical and physical changes is an unfortunate reality for paintings, and computerized methods may help with color restoration. A recent approach utilized how pixels compare to neutral gray, the reflectance, and shading values to detect cracks and they were filled in.[47]

Besides color restoration, computational image analysis has been put to work to inspect the position and direction of light source in paintings. These analyses may provide insights about a particular artist's technique. For instance, Johnson et al. studied the light source in Johannes Vermeer's *Girl with a Pearl Earring*. The linear beams passing through shadow pixels and light area pixels (cast-shadow method) was combined with an analysis of vectorial normals of contours separating light and dark regions (occluding contour analysis).[48] These analyses substantiated the belief that realist painters, including Vermeer, possessed the ability to appropriately and coherently render actual lighting information in the scene.

Affective Analysis

Affective computing, which involves the affective analysis of digital content, is yet another relatively young research field. "Affect" is the psychological state of a person during his or her sensory interactions with the environment. Computerized analysis methods have been developed to analyze the emotions that photographs and paintings elicit from viewers. For instance, affective computing methods have been applied to photographs to predict the emotions they elicit on viewers. These approaches may help with classifying a large collection of paintings into categories according to their affective content, or may provide insight into different career periods of an individual painter. Specialist methodologies have been developed to investigate the affective content of abstract paintings. Sartori et al. created professional (MART dataset) and amateur (deviantArt) abstract datasets to acquire the emotional ratings of works by human subjects. They extracted visual words from small patches in each image, which represent color and texture information. These visual words were employed to classify positive and negative emotions evoked by the paintings.[49]

Other studies considered a more complex approach to affect rather than the positive-negative separation of emotions. Lu et al. adopted a two-dimensional approach to affect in order to account for both the intensity of emotions and positivity. They leveraged adaptive learning to extend knowledge of emotional content in photographs to paintings. This approach was required because the statistical distribution of visual features was not the same for photographs as it was for paintings.[50] Inspired by the fact that artists often use triangles in their compositions to portray a dynamic, stable, and/or balanced feeling, He et al. devised a method to detect inherent triangles in portraits by analyzing line segments in pairs and measuring how close these pairs came to creating a triangle.[51] Such methods have the potential to improve our ability to understand how the composition of artworks trigger particular (often unconscious) emotional responses on the part of the viewer.

Opportunities and Challenges for Future Innovation

While we have seen a number of exciting developments in the past two decades, the field of computerized analysis of paintings is in an early stage. We believe existing work has only scratched the surface of some deep and challenging questions. First, computerized analysis will continue to offer insights to art historians. With some examples of successful collaboration, we hope there will be more close collaborations between art historians and technology researchers. As large-scale, high-quality image datasets become increasingly available, art historians can partner with technologists to define and address new research questions. As scientists developing new technologies, we are always enthusiastic about tackling art historical questions of significance.

Secondly, computerized analysis may offer useful information to artists in their own practice. With millions of images of paintings at their disposal, computers hold the promise to reveal the development of paintings, to reveal networks of influence, and to offer insight into painting techniques.

Thirdly, computerized analysis will be incorporated into painting retrieval systems, virtual museums, and designer systems so that audiences can make better use of cultural heritage. Such systems will demand technological advances in visual feature indexing, linguistic indexing, affective indexing, and explainable AI.

Finally, computer and information scientists will continue to find inspiration from working on research questions relating to painting analysis. Paintings have the ability to transcend cultural and national boundaries as well as language differences. They make people think beyond the objects or scenes depicted, elicit emotion, and engage the imagination. How can an AI understand the meaning of an artwork, appreciate its aesthetic value, interpret it, or experience the emotions it generates? Computer and information sciences will need revolutionary advances on multiple fronts, well beyond what are considered "intelligent" today, in order to confront such questions.

Notes

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