25

IMAGE PROCESSING AND COMPUTER VISION IN THE FIELD OF ART HISTORY

Nuria Rodríguez-Ortega

Art history is, to a large extent, the history of the forms and systems of production and circulation of images of cultural artifacts. The crucial connection between the founding period of art history in the nineteenth century and the invention of photography has been highlighted within the discipline. However, in this timeline, we must also include: the circulation of prints and engravings, which, for many years, were the primary means of knowing, ordering, and analyzing artistic-cultural production; and language itself, which, through the descriptions associated with the *ekphrasis* genre, provided some of the earliest images—mental imagery in this case—of the artifacts described.

If we also consider that one of the central discourses of art history has made visual matter a primary subject of study, and, consequently, that vision has become one of the main cognitive mechanisms of art historians, it is easy to understand why one of the hopes for the field resides in image processing and computer vision technologies. Until recently, these technologies have had limited applications in art history, but developments in the ability of computer algorithms to process images (especially in the field of computer vision), deep learning techniques (a branch of the artificial intelligence revolution), increases in hardware processing capacity, and an ever-growing amount of visual data open up new paths of exploration. We are witnessing a turning point in digital art history to the extent that we are now able to directly process visual information rather than metadata, which has been the fundamental focus to date.

The field is still emerging, with studies that are more experimental than conclusive in their results. Yet, this new scenario deserves special attention for two reasons: (1) it opens up a rich field of research possibilities, locating the history of the culture of images that we have called "art history" in a new order of scale and complexity; and (2) it entails important intellectual challenges that impel us critically to reconsider our object of study, the methodological principles on which research about art images has rested thus far, and the visual-formal problems that have concerned us for centuries. Without delving into technical details, the purpose of this paper is to provide insight into this field, considering both perspectives from an art historian's point of view and debating some key issues that might shape art historians' agenda in coming years.[1]

Overview of Current Applications in the Field of Art Images

A short overview of the possibilities of visual-formal analysis provided by image processing technologies outlines the promising future of artistic-visual studies.[2] These technologies

(Convolutional Neural Networks (CNN), computational pattern recognition, visual instance retrieval, etc.) are able to automatically recognize specific motifs, objects, figures, details, or particular image regions in large iconographic collections, and to select and group images accordingly;[3] to perform semantic-level predictions, that is, to recognize object categories, human body postures, and activities in a scene;[4] to detect visual-formal similarities and differences in large sets of images;[5] to quantify and measure the degree of similarity and difference between images;[6] to find visual-formal patterns in large image corpora;[7] to calculate and rank visual com- plexity grades:[8] to group images according to visual family resemblance;[9] to measure and rank low-level (e.g. color, texture, brightness, shadow) and high-level (e.g. movement, facial expression, interactions) visual features; and many others.

Many of these technologies have found applications in the optimization of processes of automatic classification or pre-classification of large sets of images;[10] the detection and categorization of pictorial styles;[11] the detection of copies, duplicates, and derived images in repositories and collections;[12] and the detection of painting's date of production. Likewise, they are being used for authentication and attribution, applying methodologies that closely follow the stylometric techniques used in the fields of linguistics and literature studies for authorial attribution.[13] In all these cases, the final purpose is the implementation of computational tools not only intended to support art historians' activities, but also to provide additional objectivity derived from quantitative and computational processes.

Beyond these computer-aided practices, the introduction of image processing technologies in art history also enables us to address issues that are part of the intellectual and critical concerns of the discipline and that are not alien to the methodologies that have guided the analysis of images since the early nineteenth century. For example, these technologies enable the investigation of the combinatorial mechanism that underlies image-building practices during specific time periods. Elizabeth Honig and her team, as part of their ongoing Brueghel Catalogue Raisonné Project,[14] are using these techniques to analyze the intricate web that comprises the thousands of paintings, prints, and drawings produced in the Brueghel family workshop, where copying, variations in the same formal schemes, and the production of compositional patterns using individual motifs was a systematic practice (see Figure 25.1).[15] To the extent that the methods employed in this project can be used to analyze other artists and periods, the results will help

Figure 25.1 Similar content across different styles and contexts in Jan Brueghel's image repository.

Source: Ginosar et al.,"The Burgeoning Computer-Art Symbiosis," XRDS 24, no. 3 (Spring, 2018): fig. 2.

develop a new perspective on ideas regarding originality, creativity, and invention as triggering mechanisms of the image-production process.

The possibility of detecting the reuse of similar elements in diverse images that range over time and space will allow us to place artworks in a much broader framework of comparison; delve into the visual genealogy of paintings; explore the mobility of visual elements; track the circulation of patterns and motifs; analyze processes of cultural re-appropriation of forms, figures, and patterns; examine mechanisms through which the same visual elements produce different meanings when they are placed in different context;[16] retrace the evolution of a specific pictorial motif and its variants; reconstruct connections between workshops and artists; unveil image transmission networks;[17] and explore the material conditions that make possible such transmission (e.g. when image processing techniques are able to discriminate between similar prints produced by different woodblocks).[18]

The possibility of tracking similarities and changes in motifs, visual structures, and compositions over time and unveiling the patterns that have shaped our visual culture[19] allow us to address issues about the evolution, transformation, or persistence of taste and the perception of beauty; and bring to an unprecedented scale Warburg's investigations of the persistence of the images or Kubler's investigations about the serialization of images.[20] It also assists in examining discuss processes of canonicity or mainstreaming according to the greater or lesser concentration of similar images in collections.[21]

The ability to discover the essential forms and compositions that underlie the variety of images that constitute visual culture through processes of mathematical abstraction allows us to explore fundamental concepts that have shaped the intellectual tradition of art history. Thus, for example, the project completed by the Uruguayan visual artist Vladimir Muhvich, *Engrama*, recovers the Warburgian notion of "cultural engram"[22] to analyze the latent visual-formal schemes in certain collections of images.[23] To do this, Muhvich generated models of morphological and evolutionary visualization of the collections on the basis of clustering information under mathematical models which are displayed in the topography of a graph (Figure 25.2).

Within this framework, *The Origin of Forms in Art* (1965), where Read affirmed that artistic forms can be formalized and reduced to certain shapes, also comes to mind. Even more, we might explore the idea of visual universals, namely the visual-formal units that are the basis of the configuration of artistic images and perhaps of our cognitive structures—those through which we understand the world. Such explorations echo Riegl's general laws[24] and the neo- Kantian stylistic categories systematized by Wölfflin.[25] Not coincidentally, both art historians' works have been used as theoretical frameworks by researchers aiming to discover by means of physico-mathematical principles, to which I will return in the following sections, the logic that governs the formation and evolution of the images of the artistic culture.[26]

Critical and Intellectual Debates

Along with new research opportunities, the introduction of image processing algorithms and computer vision techniques entails significant intellectual challenges for art historians. Such technologies necessitate epistemological and methodological redefinitions of the way images are understood and analyzed, and this demands critical inquiry. This task is not new because art history has frequently had to construct methodologies for visual-formal analysis and to develop theories about the nature of cultural images and their functioning—a task that we must now locate within the epistemological horizon of a new logic (mathematical), a new rationality (algorithms), and a new scale. I will briefly examine the issues that I consider most relevant and that will require attention in the coming years.

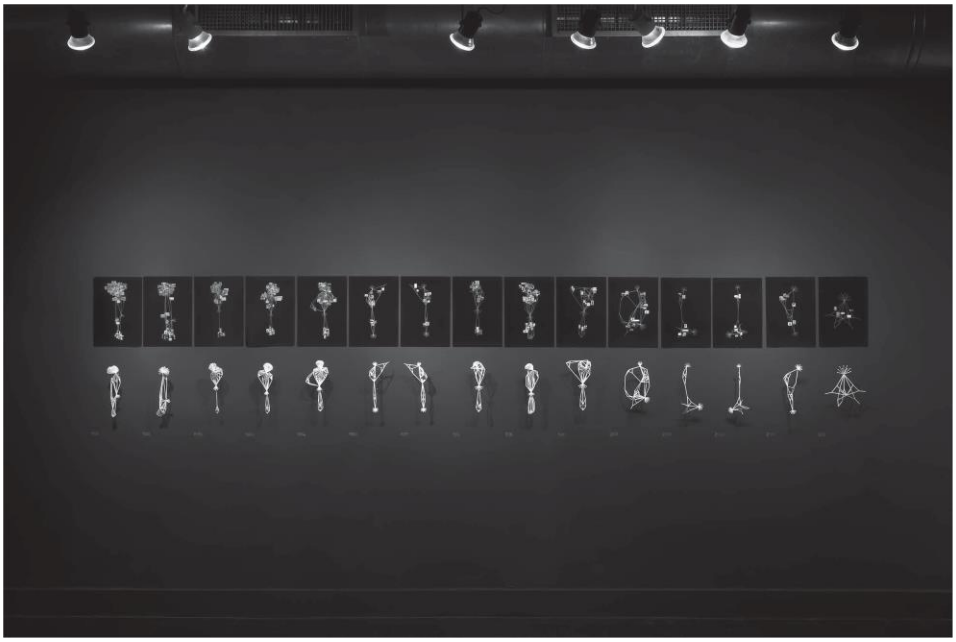

Figure 25.2 Vladimir Muhvich. Proyecto Engrama Oficial del Campo del Arte Uruguayo II, Montevideo, Uruguay 2015. *Source*: © Photograph: Martin De Rossa.

The Matter of Quantification

The theoretical-scientific approaches that conceptualize the act of seeing as a series of information processing tasks[27] and the ontological shift implied in the nature of the digital image (our new object of analysis) have profound effects. Although the reconstitution of the image on a screen can obscure this, digital images are simply a mass of information in the form of bytes and pixels, a binary code of numbers. The visual features of cultural artifacts, when digitized, are transformed into visual data, which are numerical values that can be algorithmically computed and segmented into discrete information units. This ontological shift entails a dramatic change in the way we understand images considering that, until now, images have been presented to our consciousness as visual entities unto themselves.[28]

It is important to be aware of this transformation because sometimes the words we use to name phenomena and the rhetoric we employ to explain them can be confusing or misleading. As Harald Klinke notes, "the computer knows no image, only numbers. It does not 'see'—it only calculates."[29] Or perhaps we could better say that the way computers see is by calculating. It is therefore crucial to consider that image processing algorithms are mathematical equations and that computer vision, based on mathematical models of human visual perception, is designed to extract data from the real world and to transform it into numerical or symbolic information.[30]

This ontological change implies that the image becomes a mathematical problem. So, one of the key questions that we have to face is how to adequately describe an image in mathematical terms. Correspondingly, formal-visual analysis becomes a problem of quantification, mathematical calculation, and measurement. This is why the style of an artist can now be defined as a statistical model of visual characteristics and the image as a statistical set of visual features. This quantitative perspective also means that investigations based on image processing focus on visual features that are easily quantifiable (such as color saturation, brightness, brushstrokes, and texture) and that physical–mathematical concepts (such as fractal dimension, entropy, and roughness exponent) are increasingly used to describe the structures, visual configuration of images, and their historical evolution.[31]

Consequently, the aspects of visual-formal analysis of images that formerly concerned us are now dissected according to mathematical logic. For example, in the research by Lee et al.,[32] the question posed by the authors was: How do color contrast relations evolve in Western pictorial production over a long period of time (from the fourteenth century to the present)? This question is not completely new in the field of art history, but the approach was. To answer this question, the authors designed an algorithm to compute the inter-pixel color distances' differences. This resulted in a quantity called "seamlessness (S)," which measures the color contrast and becomes a useful indicator to track the stylistic evolution of Western painting (see Figure 25.3).[33] This physical-mathematical translation implies a new formulation in quantitative terms of concepts that are part of the epistemic tradition of art history (see, for instance, the mathematical models developed in relation to the concepts of influence,[34] artistic creativity,[35] style,[36] beauty,[37] and so on). Simultaneously, it is producing an epistemological expansion to the extent that new categories are being built to explain phenomena observed through the algorithmic computation of images. In consequence, we are witnessing the emergence of a new categorical system of a mathematical and physical nature. Consider, for example, the concept of "metamorphosality" resulting from the application of the S measurement. "Metamorphosality" (a quantity that measures the degree of transformation of chromatic contrasts throughout an artist's career whether in positive terms (more color contrasts) or in negative terms (less color contrast)) enables comparisons to be made among artists according to this parameter. This formula is nothing less than a new category for interpreting artistic practice and creative processes and the evolution of visual culture. Likewise, new categories are emerging to order and classify visual-formal artifacts, such as those associated to fractality values and complexity measures.[38] I will return to this point in the next section.

This formulation of new categories for visual-formal analysis has raised controversies and critical discussions.[39] Consider the mathematical formalization of creativity proposed by Elgammal and Saleh in 2015:[40] If one of the two variables of the mathematical model proposed by the authors to measure the degree of creativity of image production is the capacity of an image to resonate in images produced later, is the idea of creativity being modeled or is this closer to

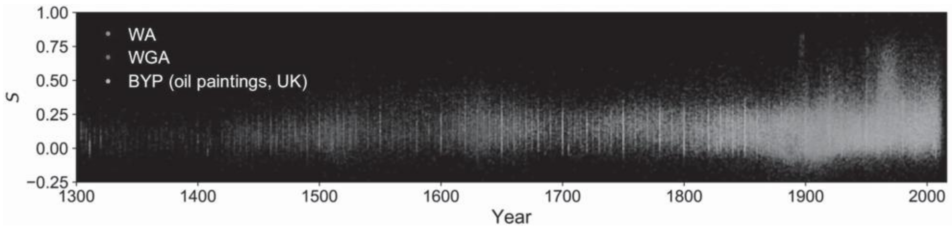

Figure 25.3 Scatter plot of S from 1300 CE to 2400 CE. An increase in the average and the variance of S is observed.

Source: Lee, B., D. Kim, S. Sun, H. Jeong, and J. Park. "Heterogeneity in Chromatic Distance in Images and Characterization of Massive Painting Data Set." *PLoS One* 13, No. 9 (2018), e0204430. https://doi.org/10.1371/journal.pone.0204430, fig. 4b.

the notion of impact? Is the ability to influence others a *sine qua non* variable of creativity? We do not know whether this resonance derives from causal lines of real influences because this information is not provided by algorithmic processing; these might be autonomous, parallel occurrences without connection to each other, as sometimes occurs in complex systems. How many assumptions are being applied, then, in the interpretation of the results and in the building of the model itself? Are we simultaneously validating a paradigm of chronological sequence as an interpretation of the visual-formal dynamics of artistic imagery when using this paradigm as the basis of a mathematical model?

Similar arguments could be made regarding the research conducted by Kim et al.[41] In this study, different image processing techniques were used to quantify changes in the variety of painted colors and their spatial structures over time, producing remarkable conclusions about the historical development of colors. However, the *a priori* use of ten historical periods of Western paintings to demarcate the evolution of color (taking as a base the "traditional stylistic classification of Art History") involves projecting a certain schema that determines the research and its interpretation. Meanwhile, key concepts, such as the concept of style itself and its ability to describe and or explain the visual-formal evolution of artistic images,[42] remained uninterrogated.

As algorithms, mathematical models, and metrics have become a fundamental part of interpreting a world driven by the continuous flow of data, it is vital that art historians be involved in the development of a new understanding of images based on statistical methods, mathematical models, algorithmic indexes, and metrics. This allows us to quantitatively and qualitatively characterize visual structures and features that expand our comprehension of cultural imagery. The exploration of the appropriate measures and formal models to characterize visual structures and their features should be one of the main tasks of the art historian's future agenda. Such work needs to be undertaken in close collaboration with mathematicians, computer scientists, physics, and experts in computer vision and data science.

Maintaining this critical discussion and interdisciplinary exchange is fundamental because the analysis derived from the application of algorithms, metrics, and mathematical formulas is not only quantitative, but also qualitative. Every mathematical formalization implies a concep- tual model—that is, an intellectual construction through which the domain of reality that is being modeled (its entities, variables, functions, parameters, and relationships) is represented. If we are talking about formal–visual analysis within the framework of art history, what is implicit in these analyses is a certain theory about the image, the evolution of imagery, and modes of vision.This is why analysis based on the computational processing of images should be consid- ered not only as the application of mathematical, physical, and/or statistical formulas, but as a theoretical construction of what could, and perhaps should, emerge as a new image and visuality theory. It also demands awareness of the epistemological and ideological determinations that are embedded in the analysis strategies we are using.

Complementarily, a new vocabulary needs to be created to name the new phenomena that emerge from image processing. It is important to elucidate new concepts in connection to existing art history epistemology, and one way to do so is to develop a vocabulary that allows us to name the phenomena that become relevant for the visual–formal analysis. Consequently, elucidation, disambiguation, and terminological clarity are also crucial tasks for art historians in the coming years.

Finally, this mathematical translation requires further reflection on how the way in which we look at images is affected. Art historians also need to adopt a critical position to think about what remains irreducible to quantification and computation[43] and what cannot be explained in quantitative terms.

Scale and Complexity

The change of scale associated with the analysis of large sets of images that expand over time and space is also revolutionizing our understanding of image analysis. In this new scenario, several questions need to be considered. First, some problems concerning large-scale databases or repositories that are used as the basis of analysis must be addressed.[44] This concerns, for example, whether available data sets are sufficiently diverse from a cultural point of view to allow us to perform analyses on a truly global scale and not exclusively at the Western level. Consideration needs to be given to differences in access to image databases according to countries and regions; copyright issues; the heterogeneity of image quality grades; differences in accuracy labels; and the limited nature of many collections that are composed exclusively of images from a particular art "tradition."

Second, large-scale databases and repositories of images confront us with new possibilities of exploration that allow us to map culture on a global scale: diversity, structures (networks, clusters, relationships, etc.); dynamics (temporal changes); and variability.[45] This is what we essentially seek to uncover when we analyze large-scale image collections. Consequently, the fundamental questions of art history in relation to images and visuality must be reformulated within this broader paradigm of cultural interpretation.

In the context of visual studies, the bibliography on the new ecology of images that emerged from the explosion of visual media and the internet is vast. However, the possibility of materializing and quantifying visual connections between these images, forms, compositional structures, and motifs allows us to approach the ecology of images from the perspective of complex systems. This includes establishing degrees of proximity and similarity, neighborhoods, lines of contagion; and unveiling structures, dynamics, interactions, and logic of behavior over time through the use of mathematical models, advanced computing, simulations, and physics-inspired approaches. Thinking about visual imagery in terms of complex systems involves becoming aware that we can confront systems that are n-dimensional, nonlinear, self-organized, open, interdependent on other systems (adjacent or not), dynamic, and of increasing complexity.[46]

It is important to keep in mind that complexity is not an attribute belonging to the ontological nature of a certain reality. Complexity is a behavior that can be observed in the visual-formal configuration of a single image, in a set of images,[47] or at a large scale.[48] The approach to images and artistic forms from the perspective of complexity has been the subject of much scientific literature, most of which has been developed in Departments of Physics, Mathematics, Computer Science and Psychology. "When regarding an artistic form, the challenge to the complexity scientist is to address two basic questions: How do we define and characterize the system-theoretic fingerprints of an artistic form and how can we actually measure them?" argue physicists Boon, Casti, and Taylor.[49] However, from the point of view of art history, the question is not only a matter of quantity or measurement. The fundamental question is how complexity can provide us with renewed epistemic and methodological tools to address the intellectual problems that have been part of the tradition of art history, while also enabling us to expand our interpretative horizon and to explore new narratives.

Complex systems allow us to expand the notions of temporality that we have used to explain the evolution of images, their formal qualities, and the links between them. In an effort to build a narrative of the history of images and their features, art history has formulated operating principles, established explanatory cultural categories, and explored the causes of formal transformation. The approach of complex systems encourages the exploration of such processes, taking the evolutionary dynamics of increasing complexity and order-disorder transitions as a basis. This leads us to question whether the imagery produced by a particular artist or in a particular cultural context or temporal range evolves toward increasing complexity, insofar as the combination of elements becomes more unpredictable and random or more ordered and regular. What kind of complexity characterizes the evolution of artistic images and forms over time? What are the best measures for accounting for such complexity? What are the moments of rupture and disorder that give rise to new creation and, therefore, enable evolution and how are they produced?

In this context, the research conducted by Sigaki, Perc, and Ribeiro[50] is of interest. Applying two measures of complexity associated with the local order of the pixel arrangement in almost 140,000 visual artworks (the normalized permutation entropy and the statistical complexity), the authors built a complexity–entropy plane. This is a quantitative and qualitative space that can be understood as an order–disorder plane, where a set of artworks is located according to the average values of such measures. Figure 25.4 shows the artistic styles displayed on this plane, demonstrating a distribution that breaks the traditional narrative of stylistic sequencing and giving rise to new forms of organization.

Networked systems that emerge from algorithmically computed visual-formal connections generate a framework of spatial and morphological analysis that is not historical in the chronological sense. The questioning of time as a sequential structure is by no means new in the field of art history. Examples include Warburg's transchronology positioning,[51] Didi-Hubermas's critical revision,[52] and Moxey's notion of heterochronies.[53] In addition, numerous artistic facts challenge the narrative of time as a succession.[54] The acknowledgment of the existence of formal breaks

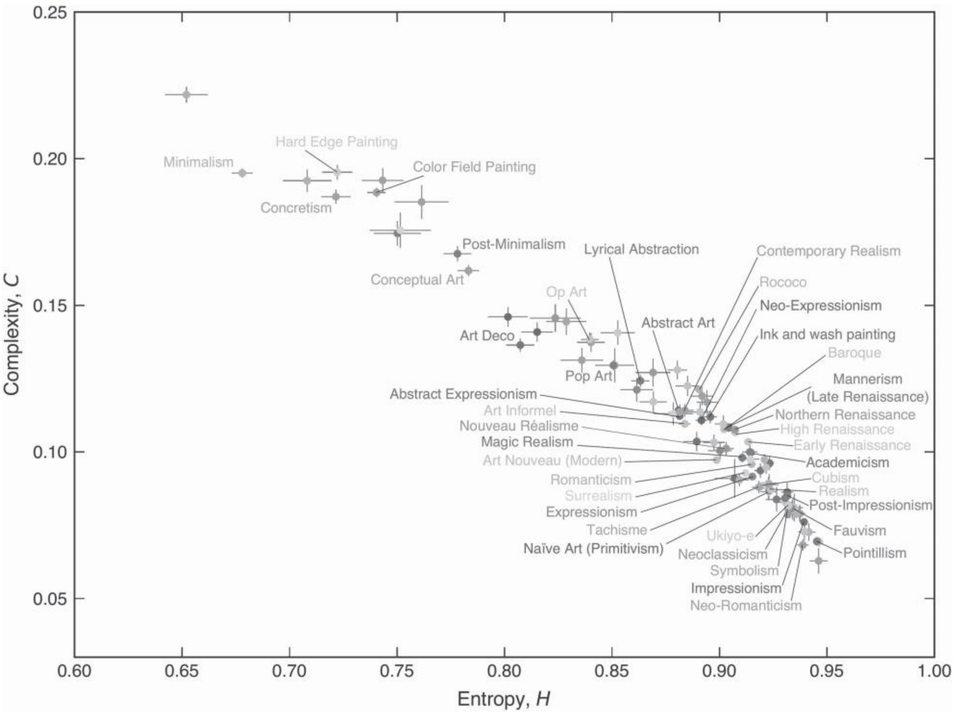

Figure 25.4 Distinguishing among different artistic styles with the complexity–entropy plane.

Source: Sigaki, HigorY.D., Matjaz Perc, and HaroldoV. Ribeiro."History of Art Paintings Through the Lens of Entropy and Complexity." PNAS 115, no. 37 (July 19, 2018): fig. 2.

and discontinuities call into question the paradigms of chronological sequencing and causality, chains of influence, the resolution of formal problems, and genetic succession or formal genealogies. What the science of complexity and its related theories offer us are methodological and epistemological tools to interpret these qualitative leaps, such as the notion of "emergence," already applied to explain social phenomena.[55]

As noted earlier, the interpretation of the networked systems built from visual connections between images is based on interpreting the clustering set's distribution or the graph's morphology. In a graph or set of clusters, similarities or differences between images are based on values of distance calculated mathematically in a metric space. There are, however, also related to the position of the elements and their established spatial relationships. The geographical and geopolitical space in which images and forms circulate becomes, therefore, a qualitative and symbolic space that is constructed by the images themselves in their continuous process of interaction.[56] Thus, interest shifts from the characteristics or attributes that define the images as entities in themselves to the functional dimensions and interactions through which the space of image is configured and reconfigured.

Complexity science and its related theories[57] open up a wide range of research lines, offering models and theories to analyze not only the transformation of simple forms into qualitatively more complex forms, but also the discontinuities, bifurcations, leaps, and occurrences that cannot be explained from the point in view of classical logic. However, it is the responsibility of art historians to determine the limits of these models and theories. Some analyses based on fractal geometry (which explains natural phenomena very well) do not serve to explain cultural, social, or visual behavior.[58] Yet, if formal and mathematical models account for structures and dynamics underlying the world we inhabit, approaching the analysis of images from this perspective will help us to understand our universe better and will make us more aware of the intricate and evolving network of structures and connections that comprise it.

Decentering the Human

Another fundamental transformation that we must consider is the change in knowledge production systems. In our post-digital era, these have become a hybrid ecology in which the human being no longer holds the central position. Assuming the end of the encephalocentric paradigm (i.e. the limitations of the human brain to see, understand, and explain the dynamics of complex processes) entails a process of disembodiment and decentering of the subject (in our case, the art historian) as the center of vision and interpreter of images. This new condition implies the need to ask ourselves broader questions: What does it mean to see in the era of computer vision? Where is human vision resituated in its relationship with the world in general and, in particular, to the images of the artistic culture? What will our new role as art historians be in a knowledge production system in which human beings, non-human beings, programming languages, and algorithms are equally involved in the production of knowledge about visual materials? Thus, the technological developments of our time place the problems of art history and visual studies at the center of the debate: the problem of vision, of the perceptual relationship between the object seen and the subject who sees, and the construction processes—political, social, and cultural—of the gaze.

Since technological devices influence ideas about cultural production and generate different visual paradigms,[59] the mediation of artificial devices creates new spaces for critical dis- course. Although some theoretical approaches posit that the way machines see is objective, computer vision is not neutral. It, too, is constructed vision. The artificial gaze is not subject to the conditions of human perception or its subjectivities, but other mechanisms come into play:

Algorithms that follow certain criteria or the set of images used for deep learning techniques are just two examples.

I previously referred to the selection mechanisms used by Google Images as a factor to be considered in the process of building visual imagery in the twenty-first century.[60] The situation has become more complicated given the ubiquity and opacity of artificial devices that process millions of images on the internet. This gives rise to new responsibilities. For example, photography platforms are programmed to select images from the millions that are shared daily by users according to automated evaluation technologies based on artificial intelligence. These technologies aim to estimate the aesthetic quality of the image without any user involvement (Automatic Aesthetic Quality Estimation).This task of evaluation, through which a certain average aesthetic rating is assigned to a photo, implies the definition of a good photograph and the qualities that make it so.[61] Part of image processing is based on millions of data points contributed by users according to elements that they find attractive or aesthetically rewarding. The final result depends, however, on a non-transparent algorithm that determines certain aesthetic evaluation criteria as valid. Consequently, we are not only witnessing the construction of a system of aesthetic values and taste based on the logic of algorithms, but also a scenario that compels us to think of these new aesthetic forms as a new cultural hegemony that is transferred through artificial intelligence systems. It is necessary to explore the channels (institutional, formal, informal, etc.) through which they circulate, how this hegemonic aesthetic system is reinforced as artificial devices continue learning from the new inputs contributed by users, and how this new scenario will affect the concept of aesthetics and its perception.

Given the constructed nature of artificial vision, the processed images returned to us by neural networks or computer vision algorithms constitute a determined interpretation of the processed visual materials that are subjected, in turn, to numerical transformation in the course of digitalization. Art historians will later focus on this visual material that has already been "interpreted." What then emerges is an interpretative-hermeneutic dynamic that becomes more complex because humans and artificial devices are involved in its articulation. Some may argue that the photographic images on which the work of art historians was based during the nineteenth century and a good part of the twentieth century are also interpretations of the cultural artifacts they represent. This is so, but it is important to remember that it is the human eye and brain that operate behind a camera which has no capacity for autonomous choice.

Mediation by artificial vision devices requires us to understand how artificial intelligence and computer algorithms work. It forces us to ask ourselves how the intellectual mechanisms that we have traditionally used to analyze, categorize, classify, and interpret art-historical images change when they are conducted by algorithmic calculations and neural networks without direct human interaction. The good news is that understanding how artificial intelligence works and how algorithms and neural networks develop their understanding of images may be fruitful for the field of art history and for enhancing our comprehension of the behavioral logic of artistic visual culture.

First, computer vision confronts us with what occurs in the precognitive stage of vision—what happens before culturally weighted cognition affects visual perception. In the pre-cognitive stage, shadows, surfaces, areas, shape limits, etc. are recognized. These visual characteristics are essential to distinguishing a human form from an object, as we can now see through the functioning of neural networks. The systems of image analysis developed in the context of the Western theory of art history had considered visual-cognitive perception, so should we now also incorporate this other pre-cognitive dimension? In this sense, Harald Klinke[62] has proposed expanding the layers of analysis on Panofsky's triadic scheme. Yet this question requires further reflection.

Second, these technologies also compel us to rethink crucial concepts in visual analysis. I am not only referring to art-historical concepts (e.g. the notion of style transformed into a statistical model of visual features as mentioned earlier), but more essential concepts such as similarity or analogy that are key components of the logic that underlies computer vision analysis. This is not a trivial question if we consider that the task of finding similarities and differences among images is the basic intellectual activity upon which art history is built. The capacity of algorithms and computer techniques to analyze complex information allows us to consider many more visual features than our human brain can process. Consequently, art historians now have the opportunity to explore more deeply variations of "similarity." However, as Mathew Lincoln has stated,[63] we first need to understand what similarity means in computational terms. We need to understand the notions of similarity, difference, proximity, and resemblance as seen through neural networks and algorithms.

Third, insofar as technologies advance without human supervision, we also need to reflect on how the artistic-visual universe will change once concepts traditionally used for image classification or description are replaced by computational processes. For instance, how do we confront the units, patterns, correlations, and visual regions generated by computer vision algorithms that exceed the traditional notions of forms, motifs, and topoi that have formed the basis of our image analysis to date?

Despite a possible destabilization of our traditional visual regimes, these new ways of seeing have a heuristic value of which we should take advantage. The ways in which algorithms see, interpret, and classify images draws attention to visual-formal aspects that have hitherto gone unnoticed. In turn, these visual units, observed as a whole and grouped according to their degree of similarity, acquire new meaning. As Pilar Rosado[64] has demonstrated through her research on Miquel Planas's work, these units configure the creator's visual vocabulary, and their combinatorial patterns help us to understand his creative process (see Figure 25.5). Thus, computer vision algorithms entail the emergence of a new formal vocabulary and a new method of cataloging, recording, or ordering. These tasks can, however, only be completed in collaboration with artificial devices that will generate the visual units on which we will work in the coming years.

Examining how algorithms or neural networks see leads us to rethink our own observation processes. In this way, the hermeneutic-critical system to which I referred previously becomes an iterative cycle: The observation of images as they are seen by artificial intelligence modifies our own way of observing and transforms our visual understanding. One of the aims of the Cátedra Picasso Fundación Málaga of the University of Málaga, is to use computer vision techniques for the purpose of analyzing developments in Pablo Picasso's drawings that comprise his *Album 7*.[65] The key question that triggered the research arose when we saw the first output delivered by the neural network. We asked ourselves what changes in our modes of perception and visual comprehension occur when the morphology of Picasso's drawing is analytically segmented into its formative attributes (see Figure 25.6). The result was a new observational process based on the analysis and categorization of graphic and formal units within Picasso's sign vocabulary and the exploration of its combinatorial logic and transitions to more complex forms. The comparison between the result of human observation and that of artificial observation will be the first research output of the project and the basis of the methodological process. The comparison between how human cognition is configured and how computational devices produce knowledge provides an unprecedented opportunity to deepen the mechanisms of vision. It also enables us to unravel different cultural and epistemological layers that intersect in human seeing. For example, grouping images into dendrograms not only enables a sort of visual phylogenetic reconstruction of objects, but also challenges the criteria used by the algorithm to elucidate the patterns and/or relationships that go unnoticed by the human eye.

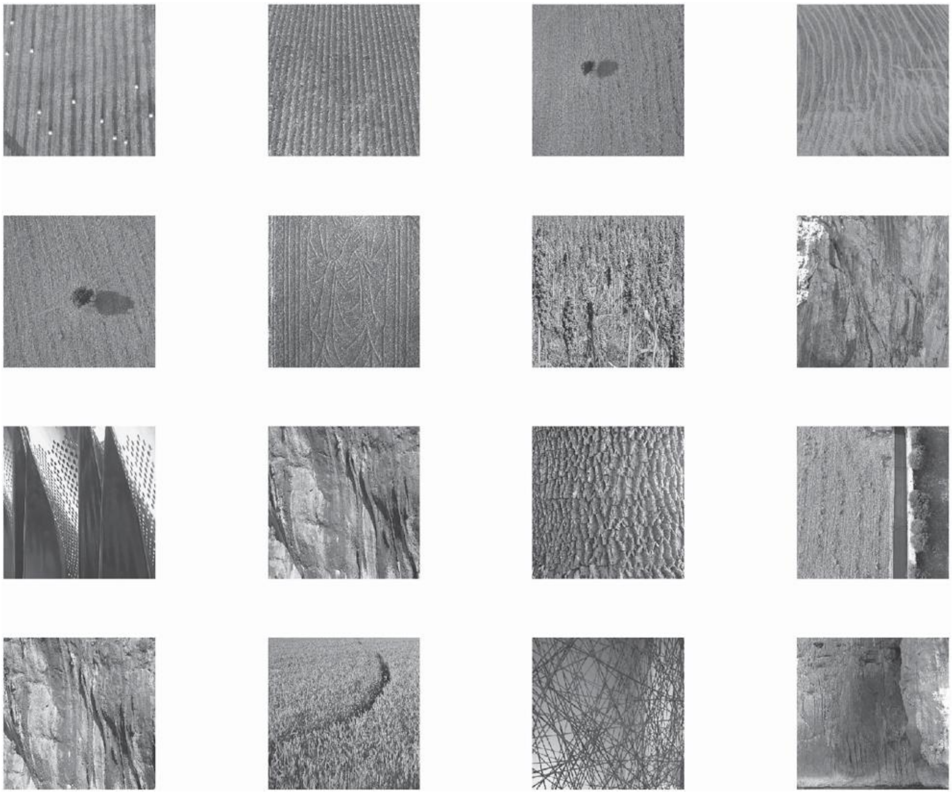

Figure 25.5 Set of sixteen images grouped by the visual appearance "Vertical irregular textured" in Miquel Planas's photograph collection.

Source: Rosado Rodrigo, Pilar. "Formas latentes: protocolos de visión artificial para la detección de analogías aplicados a la catalogación y creación artística." PhD dissertation, Universidad de Barcelona, 2015: fig. 3.31.

And fourth, collaborating with experts in computer vision within the framework of deep learning interpretability (the research field devoted to unraveling neural networks and algorithms) may be of interest for art historians who wish to understand the features that shape artistic imagery and provoke its changes over time. In so doing, researchers participate in the building of a future "explainable artificial intelligence" (XAI).[66] Researchers may also create their own models of computer vision based on theories of vision that facilitate the exploration of ways of seeing in other historical-cultural periods. An example is the recent prototype developed by Leonardo Impett based on seventeenth-century theories of vision.[67]

On the other hand, the logic underlying image processing and computer vision techniques based on strictly visual and morphological criteria is producing a sort of neoformalism or neovisualism in the field of art history. This includes the recovery of formalist theories embedded in the foundations of the discipline and that have been widely discussed and revised, such as those of Wölfflin or Riegl. We have the opportunity to write histories of visual morphologies independently of social, cultural, and historical contexts, and independently of the semantic determinations attached to language that have traditionally accompanied the images. However, we have critically to consider the consequences of these trends. We know that ways of seeing, morphologies, and notions of similarities and differences are imbricated in a complex network

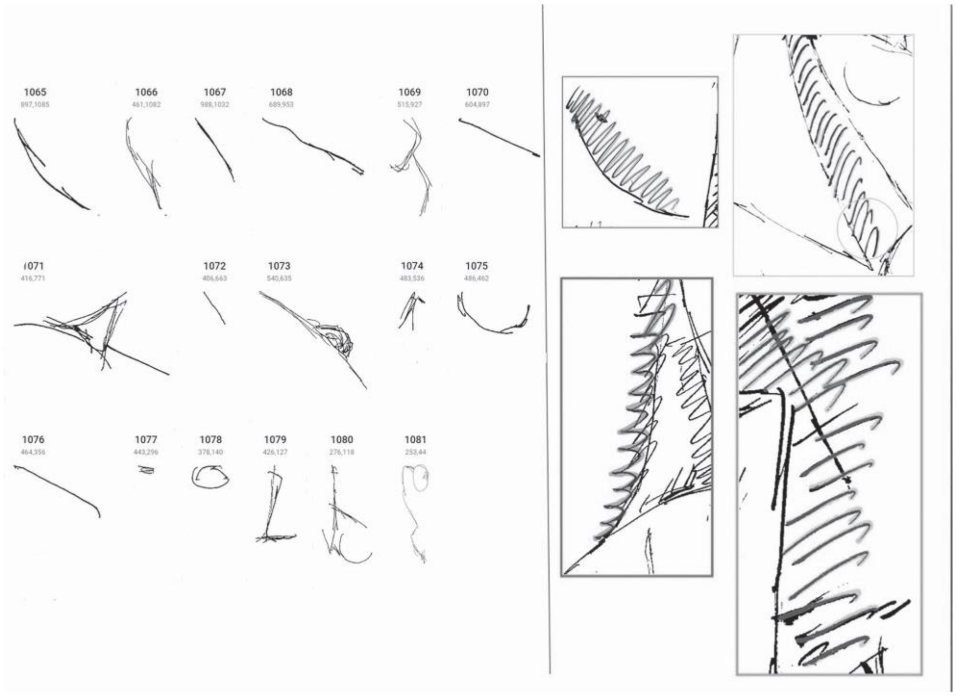

Figure 25.6 Left: Segmentation of Picasso's drawing L47R (Album 7) using an intelligent system of edge detection. Right: eye-detected and manually colored basic graphic units in Picasso's Album 7 drawings.

Source: © Cátedra Picasso Fundación Málaga.

of meanings that exceed the merely visual. Therefore, we must also foster a critical discussion about the orientation of art history in the immediate future: whether toward a lost culture (due to the way machines now work), or, conversely, whether human beings should operate as a bridge that links visual-contextual knowledge to purely quantitative-algorithmic knowledge. Perhaps a conciliation between the computational rationale and the human hermeneutic perspective is the key. In reality, this conciliation will anchor art historians in their role of unveiling cultural factors that underlie visual structures currently generated by algorithms.

The emergence of neoformal approaches have to be included in a broader redefinition of the epistemology of art history which is moving toward a formal-visual, topological epistemology based on the heuristics of generative images' morphology.[68] The processing of millions of informational units, variables, and parameters requires readable, intelligible interfaces for human beings. Diagrams, charts, and data visualizations of all kinds are becoming the common language of art-historical research when approached from a computational perspective, and they are fundamental material for interpretative–hermeneutic work.

If computer systems are capable of analyzing the multiple variables inscribed in images in ways that the human brain cannot, and if image ecosystems can be projected in multiple directions and in an infinite number of dimensions from the perspective of complex systems, it is necessary to think in terms of a new n-dimensional space (or high-feature space, in Lev Manovich's words).[69] Such a space surpasses the three-dimensional Euclidean space in which we are used to considering art images and other cultural artifacts. This compels us to address the problem of how to visualize multidimensionality without resorting to a dimension reduction, as usually currently occurs. Dimension reduction implies selecting which variables or dimensions are projected, and this confronts us with traditional problems of cultural criticism and the politics of representation. However, we must also be mindful of the impossibility of representing the totality. The question arises, therefore, as to how to achieve an equilibrium in the context of these new representational practices.

Some visualizations or meta-images (as Klinke[70] calls them, following the terminology proposed by W.J.T. Mitchell) that are being produced also raise an interpretative problem. Many of them are still just visual artifacts to play with or upon which to speculate. We still have much work to do to explore their epistemic potential and their capacity to express a theory or new construction of the visual. In this sense, we might try setting these new images in the tradition of visual epistemology that is already present in the discipline.Warburg is the first example that comes to mind, but a systematic investigation of theoretical-epistemic constructions based on visual practices could help us to discover other examples and to outline a new historiographical narrative to explain the construction of discourses about images and modes of visuality over the last two centuries.

Conclusion

In conclusion, I suggest that four questions need to be considered: (1) how images of cultural artifacts are transformed into units of computable information; (2) how the visual material that constitutes those cultural artifacts are represented in quantifiable binary code (visual data); (3) how these transformed images and visual materials coexist in an expanded field with thousands of other transformed images; and (4) how human vision is subjected to a process of decentering and disembodiment.

Within this new research scenario, computational image processing techniques provide us with an opportunity to reconnect with concepts and approaches that have been key components of nineteenth- and twentieth-century art history. Thus, art historians now have an invaluable toolkit at their disposal to explore the intellectual dialectics (transformation–persistence, sequence–simultaneity, variation–unity, diachrony–structure, and discontinuity–continuity) of visual forms, matters that have long been preoccupations of art history. These techniques also lead to broader questions about how we know, see, understand, and relate to the world. Per- haps we are now in a position to respond to the question of whether the visual-formal traits through which we identify an object are universal and objective or depend on systems of cultural representation.

Simultaneously, experimentation in close collaboration with mathematicians, experts in computer vision, and computer scientists promises fruitful avenues to redefine our understanding of images and visual culture. It also generates the possibility of a hybrid knowledge field intermediated by heterogeneous, but complementary disciplines.

The techniques and methodologies discussed in this chapter also impel us to take a critical position that involves investigating new art-historical epistemology and intellectual inquiries. Computational image processing techniques must serve as critical tools to reassess the practices, concepts, and assumptions that we have used to date in the analysis of artistic images instead of becoming a means by which perpetuate them in an uncritical way. The fundamental question to be considered is how art historians can become involved in the conversation, contributing their theoretical knowledge and points of view. A review of image processing and computer vision techniques applied to art images reveals the absence of art historians in most of the research groups.

Much of the research conducted in the field of computational image processing is guided by the ideal of transforming the exploration of images and visuality in a quantitative, scientific objective field. This involves looking for an unbiased measure of complexity in artworks as an alternative to human judgments or envisioning art history as a predictive science. These approaches are part of a trend in the field of knowledge that exceeds the limits of digital art history itself: the search for a science of culture and images based on the empirical principles of the natural, physical, and biological sciences. This approach opens up interesting lines of exploration. It is, however, also necessary to delve into the specificities of cultural, formal, and visual complexities of art image production and evolution to understand what might be the limits of these models and theories in order to explain them. Intellectual collaboration, then, becomes more necessary than ever.

Ultimately, the questions raised in this chapter draw attention to how technological materialities act as agents in the production of visual knowledge and how we need to reconcile computer reasoning and human cognition, artificial devices, and human beings. In my view, establishing spaces of convergence and collaboration is a better strategy than developing a confrontational rhetoric of human beings vs. machines. Establishing a space in which mutual feedback helps us to move toward a better understanding of ourselves as a species, of the world we inhabit, and of the culture we produce should be the main purpose of the humanist's agenda in years to come.

Notes

1. For reasons of space, I will not address the issues related to the production of post-human images by artificial devices neither the issues related to computer creativity. Nor will I address the issues concerning the subject's aesthetic response to such images or the ability of artificial intelligence to generate images that consciously appeal to the emotionality of the viewers.
2. For a general overview of the history of the field and early applications, see David G. Stork,"Computer Vision and Computer Graphics Analysis of Paintings and Drawings:An Introduction to the Literature," in *CAIP* 2009, eds. X. Jiang and N. Petkov, LNCS 5702 (Heidelberg: Springer, 2009), 9–24; David G. Stork, Jim Coddington, and Anna Bentkowska-Kafel, eds., "Computer Image Analysis in the Study of Art," *Proceedings of SPIE,* vol. 6810 (Bellingham: International Society for Optics Photonics, 2008); David G. Stork, Jim Coddington, and Anna Bentkowska-Kafel,"Computer Vision and Image Analysis of Art," in *Proceedings of SPIE,* vol. 7531 (Bellingham: International Society for Optics Photonics, 2010); David G. Stork, Jim Coddington, and Anna Bentkowska-Kafel,"Computer Vision and Image Analysis of Art II," in *Proceedings of SPIE,* vol. 7869 (Bellingham: International Society for Optics Photonics, 2011); Benjamin Zweig,"Forgotten Genealogies: Brief Reflections on the History of Digital Art History," *Digital Art History International Journal* no. 1 (2015): 39–49.
3. Elliot J. Crowley and Andrew Zisserman, "In Search of Art," in *ECCV 2014 Workshops, Part I*, eds. L. Agapito et al., LNCS 8925 (Heidelberg: Springer, 2015), 54–74, https://doi.org//10.1007/978-3-319-16178-5_4; Ginosar et al., "The Burgeoning Computer-Art Symbiosis," *XRDS Crossroads: The ACM Magazine for Students* 24, no. 3 (Spring 2018): 30–33.
4. Joseph Schlecht, Bernd Carqué, and Björnr Ommer, "Detecting Gestures in Medieval Images," *2011 IEEE International Conference on Image Processing, ICIP* (September 11–14, 2011): 1285–88, doi:10.1109/ICIP.2011.6115669.
5. Joon Son Chung et al.,"Re-presentations of Art Collections," in *ECCV 2014 Workshops, Part I,* ed. L. Agapito et al., LNCS 8925 (Springer, 2015), 85–100, https://doi.org//10.1007/978-3-319-16178- 5_6; Babak Saleh, Kanako Abe, Ravneet Sing Arora, and Ahmed Elgammal, "Toward Automated Dis- covery of Artistic Influence," *Multimedia Tools and Applications* 75, no. 7 (April 2016): 3565–91.
6. Stefka Hristova, "Images as Data: Cultural Analytics and Aby Warburg's Mnemosyne," *Digital Art History: International Journal* 2 (2017): 116–31.
7. Xi Shen, Alexei A. Efros, and Mathieu Aubry, "Discovering Visual Patterns in Art Collections with Spatially-Consistent Feature Learning," *arXiv:1903.02678v2* (March 8, 2019).
8. Alex Forsythe et al., "Predicting Beauty: Fractal Dimension and Visual Complexity in Art," *British Journal of Psychology* 102 (2011): 49–70, https://doi.org/10.1348/000710X498958; Daniel Kim,

Seung-Woo Son, and Hawoong Jeong, "Large-Scale Quantitative Analysis of Painting Arts," *Scientific Reports* 4, no. 7370 (December 2014): 1–7, https: //doi.org/10.1038/srep07370; Higor Y. D. Sigaki, Matjaz Perc, and HaroldoV. Ribeiro,"History of Art Paintings Through the Lens of Entropy and Complexity," *PNAS* 115, no. 37 (July 19, 2018): 8585–94.

9. Loan Tran, Poshen Lee, Jevin West, and Maximilian Schich,"Chromatic Structure and Family Resemblance in Large Art Collections," in *Digital Humanities 2018*, accessed July 10, 2019, https://dh2018.adho.org/chromatic-structure-and-family-resemblance-in-large-art-collections-exemplary-quantifi cation-and-visualizations/.
10. Sean Yang et al.,"Classifying Digitized Art Type and Time Period," in *Proceedings of International Journal for Digital Art History* (London, UK, August 2018), https://doi.org/10.1145/nnnnnnn.nnnnnnn.
11. Lior Shamir et al.,"Impressionism, Expressionism, Surrealism: Automated Recognition of Painters and Schools of Art," *ACM Transactions on Applied Perception* 7, no. 2 (2010); Sergey Karayev et al.,"Recognizing Image Style," *arXiv:1311.3715* (2013); Ahmed Elgammal et al., "The Shape of Art History in the Eyes of the Machine," *arXiv:1801.07729v2* (February 12, 2018).
12. John Resig,"Using ComputerVision to Increase the Research Potential of PhotoArchives,"*Journal of Digital Humanities* 3, no. 2 (Summer 2014), accessed July 1, 2019, http://journalofdigitalhumanities.org/3-2/using-computer-vision-to-increase-the-research-potential-of-photo-archives-by-john-resig/.
13. Patrice Abry, Herwig Wendt, and Stéphane Jaffard, "When Van Gogh Meets Mandelbrot: Multifractal Classification of Painting's Texture," *Signal Processing* 93, no. 3 (April 2013): 554–72.
14. "Brueghel Family: Jan Brueghel the Elder, The Brueghel Family Database," University of California, Berkeley, accessed July 10, 2019, http://janbrueghel.net.
15. Ginosar et al.,"The Burgeoning Computer-Art Symbiosis"; Shen et al.,"Discovering Visual Patterns."
16. Schlecht et al.,"Detecting Gestures."
17. Benoit Seguin, Isabella di Leonardo, and Fréderic Kaplan, "Tracking Transmission of Details Paintings," in *Digital Humanities DH2017* (2017), accessed July 1, 2019, https://dh2017.adho.org/abstracts/562/562.pdf
18. Chung,"Re-presentations."
19. Byunghwee Lee et al., "Heterogeneity in Chromatic Distance in Images and Characterization of Massive Painting Data Set," *PLoS One* 13, no. 9 (2018): e0204430, https://doi.org/10.1371/journal.pone.0204430; Javier de la Rosa and Juan-Luis Suárez,"A Quantitative Approach to Beauty, Perceived Attractiveness of Human Faces in World Painting," *Digital Art History: International Journal* 1 (2016): 112–29; Kim et al.,"Large-Scale"; Sigaki et al.,"History of Art."
20. George Kubler, *The Shape of Time: Remarks on the History of Things* (New Haven:Yale University Press, 1962).
21. Tran et al.,"Chromatic Structure."
22. 'Engram': Neurophysiological footprint in the brain that is the basis of a memory. 'Cultural engram': traces or visual symbols that are recorded in the archives of the memory of the culture.
23. "Engrama Oficial del Campo del Arte Uruguayo," accessed July 10, 2019, www.vladimirmuhvich.com/#text_block_8.
24. Alöis Riegl, *Stilfragen. Grundlegungen zu einer Geschicte der Ornamentik* (1893). Spanish translation: *Problemas de estilo. Fundamentos para una historia de la ornamentación* (Barcelona: Gustavo Gili, 1980).
25. Heinrich Wölfflin, *Kunstgeschichtliche Grundbegriffe* (1915). Spanish translation: *Conceptos fundamentales de la Historia del Arte* (Madrid: Espasa Calpe, 2007).
26. Elgammal et al.,"The Shape of Art History"; Kim et al.,"Large-Scale"; Sigaki et al.,"History of Art."
27. Edmund T. Rolls and Gustavo Deco, *The Computational Neuroscience of Vision* (Oxford: Oxford University Press, 2002).
28. It is true that the analysis of the components—whether formal or content—that constitute an image has been part of different methodological traditions of art history, but these components were always interpreted in relation to that image as an iconic unit.
29. Harald Klinke,"Big Image Data Within the Big Picture of Art History," *Digital Art History International Journal* no. 2 (2016): 21.
30. Richard Szeliski, *Computer Vision: Algorithms and Applications* (London: Springer-Verlag, 2010).
31. Richard P. Taylor, Adam P. Micolich, and David Jonas, "Fractal Analysis of Pollock's Drip Paintings," *Nature* 399 (June 3, 1999): 422; Katherine Jones-Smith, Harsh Marthur, and Lawrence Krauss, "Drip Paintings and Fractal Analysis," *arXiv*: *0710.4917v2* (October 25, 2007); Katherine Jones-Smith and Harsh Marthur, "Fractal Analysis: Revisiting Pollock's Drip Paintings," *Nature* 444 (2006): E9–E10; E. M. de la Calleja, F. Cervantes, and J. de la Calleja, "Order-Fractal Transition in Abstract Paintings,"

arXiv: 1510.06767v3 (April 12, 2019); Jean Pierre Boon, John Casti, and Richard P. Taylor, "Artistic Forms and Complexity," *Nonlinear Dynamics Psychology and Life Sciences* 15 (April 2011): 265. See also references in note 8.

32. Lee et al.,"Heterogeneity."
33. Actually, this quantity called [S] is no more than a digital extrapolation of how the artist places the color pigments spatially on the canvas.
34. Saleh et al., "Toward Automated Discovery."
35. Ahmed Elgammal and Babak Saleh, "Quantifying Creativity in Art Networks," *arXiv:1506.00711v1* (June 2, 2015).
36. Elgammal et al.,"The Shape of Art History."
37. De la Rosa and Suárez,"A Quantitative Approach."
38. See references in note 8.
39. Claire Bishop, "Against Digital Art History," *Digital Art History: International Journal* no. 3 (2016): 123–31.
40. Elgammal and Saleh,"Quantifying Creativity."
41. Kim et al.,"Large-Scale," 1–7.
42. The same could be said about the concepts of "creativity," "influence," "beauty," etc.
43. Nuria Rodríguez-Ortega, "Digital Art History: The Questions That Need to Be Asked," *Visual Resources* 35, no. 1–2 (March–June 2019): 6–20.
44. Together the image data sets made available by museums, large-scale image database frequently used are Web Art Gallery,Wikimedia, ImageNet, Google Art Project,WikiArt, Artsy.
45. Lev Manovich, "Can We Think Without Categories?" *Digital Culture G Society* 4, no. 1 (2018): 17–28, https://doi.org/10.14361/dcs-2018.0103.
46. Carlos Eduardo Maldonado,"¿Qué es un sistema complejo?" *Revista Colombiana de Filosofía de la Ciencia* 14, no. 29 (2014): 71–93.
47. See, for example, the application of complexity measures based on fractal dimensions to the Pollock's work or abstract paintings in general. In the case of Pollock's work, researcher observed a systematic behavior since the fractal dimension increased as a function of the year in which the paintings were painted. See references in note 34.
48. Lee et al.,"Heterogeneity"; Kim et al.,"Large-Scale"; Sigaki et al.,"History of Art."
49. Boon et al.,"Artistic Forms."
50. Sigaki et al.,"History of Art."
51. Aby Warburg, *Der Bilderaltas Mnemosyne,* ed. Martin Wranke and Claudia Brink (Berlin: Akademie Verlag, 2000). Spanish translation (Madrid: Akal, 2010).
52. Georges Didi-Huberman, *Ante la imagen* (Murcia: Cendeac, 2010), first published in 1999.
53. Keith Moxey, *El tiempo de lo visual. La imagen en la historia* (Vitoria Gasteiz: Sans Soleil, 2015).
54. Among others, Audrey Rieber mentions the survivals, the anachronisms, the pseudomorfosis and the recreations. Audrey Rieber, "El arte como forma de tiempo. Algunas observaciones sobre la obra de arte y la historia basadas en relfexiones de y sobre Erwin Panofsky," in *Síntomas culturales. El legado de Erwin Panosky*, ed. Luis Vives-Ferrándiz Sánchez (Vitoria-Gasteiz: Sans Soleil, 2018), 77.
55. R. Keith Sawyer, *Social Emergence: Societies as Complex Systems* (Cambridge: Cambridge University Press, 2005).
56. See, for example, the *Gesture Atlas* developed by Leonardo Impett, Biblioteca Hertziana Digital Humanities Lab, 2019, accessed July 10, 2019, https://biblhertz.github.io/atlas/.
57. Carlos Maldonado, *Complejidad de las ciencias sociales.Y de otras ciencias y disciplinas* (Bogotá: Ediciones desde Abajo, 2016).
58. Boon et al.,"Artistic Forms."
59. John Berger, *Ways of Seeing*, BBC Two (London: Penguin, 1972). Spanish translation: *Modos de ver* (Barcelona: Gustavo Gili, 1972).
60. Nuria Rodríguez-Ortega, "Mediación digital en los procesos de recepción, construcción e interpretación de la herencia cultural," in *Memoria y significado,* ed. Luis Arciniega (Valencia: Universitat de Valencia, 2013), 443–61.
61. Juan Martín Prada, *El ver y las imágenes en el tiempo de Internet* (Madrid: Akal, 2018), 125–34.
62. Klinke,"Big Image," 25.
63. Matthew Lincoln, "Holding Out for a CV Hero: The Frick Computer Vision Symposium," *Matthew Lincoln, PhD* (blog), April 18, 2018, accessed July 5, 2019, https://matthewlincoln.net/2018/04/16/holding-out-for-a-cv-hero-the-frick-computer-vision-symposium.html.

64. Pilar Rosado Rodrigo, “Formas latentes: protocolos de visión artificial para la detección de analogías aplicados a la catalogación y creación artística” (PhD diss., Universidad de Barcelona, 2015).
65. Pablo Picasso, *Album 7* (c. May–June 1907). The set of drawings are considered to be related with the work for *Les demoiselles d’Avignon* (1907).The Album belongs to Fundación Picasso Museo Casa Natal (Málaga, Spain). Eugenio Carmona, *Picasso y la escultura Africana. Los orígenes de las Señoritas de Avignon* (Tenerife:TEA, 2010).
66. Quanshi Zhang and Song-Chun Zhu, “Visual Interpretability for Deep Learning: A Survey,” *arXiv:1802.00614v2* (February 7, 2018); Leilani H. Gilpin et al., “Explaining Explanations: An Overview of Interpretability of Machine Learning,” *arXiv:1806.00069v3* (February 3, 2019).
67. Leonardo Impett,“Early Modern Computer Vision,” in *Digital Humanities 2019*, accessed July 1, 2019, https://dev.clariah.nl/files/dh2019/boa/0820.html.
68. Johann Drucker, *Graphesis: Visual Forms of Knowledge Production* (Boston: Harvard University Press, 2014).
69. Lev Manovich, “Data Science and Digital Art History,” *Digital Art History: International Journal* no. 1 (2014): 13–35.
70. Klinke,“Big Image,” 25.

Bibliography

Abry, Patrice, Herwig Wendt, and Stéphane Jaffard.“When Van Gogh Meets Mandelbrot: Multifractal Classification of Painting’s Texture.” *Signal Processing* 93, no. 3 (April 2013): 554–72.

Berger, John. *Ways of Seeing*. BBC Two. London: Penguin, 1972. Spanish translation: *Modos de ver*. Barcelona: Gustavo Gili, 1972.

Bishop, Claire.“Against Digital Art History.” *Digital Art History. International Journal*, no. 3 (2016): 123–31.

Boon, Jean Pierre, John Casti, and Richard P.Taylor.“Artistic Forms and Complexity.” *Nonlinear Dynamics Psychology and Life Sciences* 15 (April 2011): 265–83.

Chung, Joon Son, Relja Arandjelović, Giles Bergel, Alexandra Franklin, and Andrew Zisserman. “Re-presentations of Art Collections.” In *ECCV 2014 Workshops*, Part I, LNCS 8925, edited by L. Agapito et al., 85–100. Springer, 2015. https://doi.org//10.1007/978-3-319-16178-5_6.

Crowley, Elliot J., and Andrew Zisserman. “In Search of Art.” In *ECCV 2014 Workshops*, Part I, LNCS 8925, edited by L. Agapito et al., 54–74. Heidelberg: Springer, 2015. https://doi.org//10.1007/978-3-319-16178-5_4.

Daniel Kim, Seung-Woo Son, and Hawoong Jeong. “Large-Scale Quantitative Analysis of Painting Arts.” *Scientific Reports* 4, no. 7370 (December 2014): 1–7. https: //doi.org/10.1038/srep07370.

De la Calleja, E. M., F. Cervantes, and J. de la Calleja.“Order-Fractal Transition in Abstract Paintings.” *arXiv: 1510.06767v3* (April 12, 2019).

De la Rosa, Javier, and Juan-Luis Suárez.“A Quantitative Approach to Beauty, Perceived Attractiveness of Human Faces in World Painting.” *Digital Art History. International Journal* 1 (2016): 112–29.

Didi-Huberman, Georges. *Ante la imagen*. Murcia: Cendeac, 2010. (First published in 1999.)

Drucker, Johanna. *Graphesis.Visual Forms of Knowledge Production*. Boston: Harvard University Press, 2014.

Elgammal, Ahmed, Marian Mazzone, Bingchen Liu, Diana Kim, and Mohamed Elhoseiny.“The Shape of Art History in the Eyes of the Machine.” *arXiv:1801.07729v2* (February 12, 2018.)

Elgammal, Ahmed, and Babak Saleh. “Quantifying Creativity in Art Networks.” *arXiv:1506.00711v1* (June 2, 2015).

Forsythe, Alex, Marcos Nadal, Noel Sheehy, Camilo José Cela-Conde, and Martin Sawey. “Predicting Beauty: Fractal dimension and Visual Complexity in Art.” *British Journal of Psychology* 102 (2011): 49–70. https://doi.org/10.1348/000710X498958.

Gilpin, Leilani H., David Bau, Ben Z.Yuan, Ayesha Bajwa, Michael Specter, and Lalana Kagal.“Explaining Explanations:An Overview of Interpretability of Machine Learning.” *arXiv:1806.00069v3* (February 3, 2019.)

Ginosar, Shiri, Xi Shen, Karan Dwivedi, Elizabet Honig, and Mathieu Aubry.“The Burgeoning Computer-Art Symbiosis.” *XRDS Crossroads.The ACM Magazine for Students* 24, no. 3 (Spring 2018): 30–33.

Hristova, Stefka.“Images as Data: Cultural Analytics and Aby Warburg’s Mnemosyne.” *Digital Art History. International Journal* 2 (2017): 116–31.

Impett, Leonardo. “Early Modern Computer Vision.” In *Digital Humanities 2019*. Accessed July 1, 2019. https://dev.clariah.nl/files/dh2019/boa/0820.html.

Impett, Leonardo, and Franco Moretti."Totentanz: Operationalizing Aby Warburg's *Pathosforlmen*." In *Pamphlets of the Stanford Literary Lab* 16 (November 2017): 1–10.

Jones-Smith, Katherine, and Harsh Marthur."Fractal Analysis: Revisiting Pollock's Drip Paintings." *Nature* 444 (2006): E9–E10.

Jones-Smith, Katherine, Harsh Marthur, and Lawrence Krauss."Drip Paintings and Fractal Analysis." *arXiv*: *0710.4917v2* (October 25, 2007).

Karayev, Sergey, Matthew Trentacoste, Helen Han, Aseem Agarwala,Trevor Darrell, Aaron Hertzmann, and Holger Winnemoeller."Recognizing Image Style." *ArXiv:1311.3715* (July 23, 2014).

Klinke, Harald. "Big Image Data within the Big Picture of Art History." *Digital Art History. International Journal*, no. 2 (2016): 14–36.

Kubler, George. *The Shape of Time: Remarks on the History of Things*. New Haven: Yale University Press, 1962.

Lee, B., D. Kim, S. Sun, H. Jeong, and J. Park."Heterogeneity in Chromatic Distance in Images and Characterization of Massive Painting Data Set." *PLoS One* 13, no. 9 (2018): e0204430. Accessed July 5, 2019. https://doi.org/10.1371/journal.pone.0204430.

Lincoln, Matthew. "Holding Out for a CV Hero: The Frick Computer Vision Symposium." *Matthew Lincoln, PhD* (blog), April 18, 2018. Accessed July 5, 2019. https://matthewlincoln.net/2018/04/16/holding-out-for-a-cv-hero-the-frick-computer-vision-symposium.html

Maldonado, Carlos Eduardo. *Complejidad de las ciencias sociales.Y de otras ciencias y disciplinas*. Bogotá: Ediciones desde Abajo, 2016.

———."Qué es un sistema complejo?" *Revista Colombiana de Filosofía de la Ciencia* 14, no. 29 (2014): 71–93.

Manovich, Lev. "Can We Think Without Categories?" *Digital Culture G Society* 4, no. 1 (2018): 17–28. https://doi.org/10.14361/dcs-2018.0103.

———."Data Science and Digital Art History." *Digital Art History. International Journal* no. 1 (2014): 13–35.

Martín Prada, Juan. *El ver y las imágenes en el tiempo de Internet*. Madrid: Akal, 2018

Moxey, Keith. *El tiempo de lo visual. La imagen en la historia*.Vitoria Gasteiz: Sans Soleil, 2015.

Resig, John. "Using Computer Vision to Increase the Research Potential of Photo Archives." *Journal of Digital Humanities* 3, no. 2 (Summer 2014). Accessed July 1, 2019. http://journalofdigitalhumanities.org/3-2/using-computer-vision-to-increase-the-research-potential-of-photo-archives-by-john-resig/.

Rieber, Audrey. "El arte como forma de tiempo. Algunas observaciones sobre la obra de arte y la historia basadas en relfexiones de y sobre Erwin Panofsky." In *Síntomas culturales. El legado de Erwin Panosky*, edited by Luis Vives-Ferrándiz Sánchez, 69–88.Vitoria-Gasteiz: Sans Soleil, 2018.

Riegl, Alöis. *Stilfragen. Grundlegungen zu einer Geschicte der Ornamentik* (1893). Spanish translation: *Problemas de estilo. Fundamentos para una historia de la ornamentación*. Barcelona: Gustavo Gili, 1980.

Rodríguez-Ortega, Nuria. "Digital Art History: The Questions that Need to Be Asked." *Visual Resources* 35, no. 1–2 (March–June 2019): 6–20.

———."Mediación digital en los procesos de recepción, construcción e interpretación de la herencia cultural." In *Memoria y significado,* edited by Luis Arciniega, 443–61.Valencia: Universitat de Valencia, 2013.

Rolls, Edmund T., and Gustavo Deco. *The Computational Neuroscience of Vision*. Oxford: Oxford University Press, 2002.

Rosado Rodrigo, Pilar."Formas latentes: protocolos de visión artificial para la detección de analogías aplicados a la catalogación y creación artística." PhD diss., Universidad de Barcelona, 2015.

Saleh, Babak, Kanako Abe, Ravneet Sing Arora, and Ahmed Elgammal. "Toward Automated Discovery of Artistic Influence." *Multimedia Tools and Applications* 75, no. 7 (April 2016): 3565–91.

Sawyer, R. Keith. *Social Emergence: Societies as Complex Systems*. Cambridge: Cambridge University Press, 2005.

Schlecht, Joseph, Bernd Carqué, and Björn Ommer."Detecting Gestures in Medieval Images." *2011 IEEE International Conference on Image Processing, ICIP* (September 11–14, 2011): 1285–88. doi:10.1109/ICIP.2011.6115669.

Seguin, Benoit, Isabella di Leonardo, and Fréderic Kaplan. "Tracking transmission of details paintings." In *Digital Humanities DH2017* (2017). Accessed July 1, 2019. https://dh2017.adho.org/abstracts/562/562.pdf

Sigaki, Higor Y. D., Matjaz Perc, and Haroldo V. Ribeiro. "History of Art Paintings Through the Lens of Entropy and Complexity." *PNAS* 115, no. 37 (July 19, 2018): 8585–94.

Shamir, Lior,Tomasz Macura, Nikita Orlov, D. Mark Eckley, and Ilya G. Goldberg."Impressionism, Expressionism, Surrealism: Automated Recognition of Painters and Schools of Art." *ACM Transactions on Applied Perception* 7, no. 2 (2010): 1–17. http://dx.doi.org/10.1145/1670671.1670672.

Shen, Xi, Alexei A. Efros, and Mathieu Aubry. “Discovering Visual Patterns in Art Collections with Spatially-Consistent Feature Learning.” *arXiv:1903.02678v2* (March 8, 2019.)

Stork, David G.“Computer Vision and Computer Graphics Analysis of Paintings and Drawings. An Introduction to the Literature.” In *CAIP* 2009, edited by X. Jiang, and N. Petkov, 9–24. *LNCS* 5702. Heidelberg: Springer, 2009.

Stork, David G., Jim Coddington, and Anna Bentkowska-Kafel, eds. “Computer Image Analysis in the Study of Art.” In *Proceedings of SPIE*, vol. 6810. Bellingham: International Society for Optics Photonics, 2008.

———, eds.“Computer Vision and Image Analysis of Art.” In *Proceedings of SPIE* 7531. Bellingham: International Society for Optics Photonics, 2010.

———, eds. “Computer Vision and Image Analysis of Art II.” In *Proceedings of SPIE* 7869. Bellingham: International Society for Optics Photonics, 2011.

Szeliski, Richard. *Computer Vision: Algorithms and Applications*. London: Springer-Verlag, 2010.

Taylor, Richard P., Adam P. Micolich, and David Jonas.“Fractal analysis of Pollock’s drip paintings.” *Nature* 399 (June 3, 1999): 422.

Tran, Loan, Poshen Lee, Jevin West, and Maximilian Schich. “Chromatic Structure and Family Resemblance in Large Art Collections.” In *Digital Humanities 2018*. Accessed July 10, 2019. https://dh2018.adho.org/chromatic-structure-and-family-resemblance-in-large-art-collections-exemplary-quantification-and-visualizations/.

Warburg, Aby. *Der Bilderaltas Mnemosyne*. Edited by Martin Wranke and Claudia Brink. Berlin: Akademie Verlag, 2000. Spanish translation: Madrid: Akal, 2010.

Wölfflin, Heinrich. *Kunstgeschichtliche Grundbegriffe* (1915). Spanish translation: *Conceptos fundamentales de la Historia del Arte*. Madrid: Espasa Calpe, 2007.

Yang, Sean, Bum Mook Oh, Daniel Merchant, Bill Howe, and Jevin West. “Classifying Digitized Art Type and Time Period.” In *Proceedings of International Journal for Digital Art History*. London, August 2018. https://doi.org/10.1145/nnnnnnn.nnnnnnn

Zhang, Quanshi, and Song-Chun Zhu. “Visual Interpretability for Deep Learning: A Survey.” *arXiv:1802.00614v2* (February 7, 2018).

Zweig, Benjamin.“Forgotten Genealogies: Brief Reflections on the History of Digital Art History.” *Digital Art History. International Journal* no. 1 (2015): 39–49.