PART OF A SERIES ON HOW ENGINEERING SUPPORTS THE CREATIVE INDUSTRIES AND ARTS


Figure 1

# Engineering and Cultural Heritage Conservation and Attribution of Artworks

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## Introduction

In 2021, the global artwork market was estimated to be worth $67.8B. In order to sustain this market, especially in light of the high incidence of fake artwork recently discovered in museums as well as meet societal culture goals, conservation organizations and attribution processes use technologically advanced tools in their tasks.

## Cultural Heritage Conservation

The American Institute for Conservation and the Foundation for Advancement in Conservation defines conservation as encompassing "all those actions taken toward the long-term preservation of cultural heritage for future generations. Activities include examination, documentation, treatment, and preventive care, supported by research and education."[1] Conservators can specialize in a specific area such as archaeology, artworks, book and paper, architecture, electronic media, etc. Based on the specialty, specific tools are used in artwork preservation and attribution. These tools range from micro destructive sampling techniques, to non-destructive imaging techniques, to the use of machine language processes for algorithm development in attribution and image processing. All of these tools and techniques are very similar to those used in other industries, they are merely applied for use in the art world.

## Sampling and Sample Testing

Before the use of non-destructive imaging and computational techniques in the field of cultural heritage conservation and attribution, micro samples were taken of the artwork in question and then studied microscopically or with a mass spectrometer. These tests would be used to determine the types of materials used by an artist, for example, the palette they used, the substances in the paint used to derive the pigments, the surface preparation for their painting, and any degradation that could be detected over time.[2] They could also help to date the artwork, assisting in the attribution task. The samples and their analysis also assist conservators in determining what material they should use when conserving or preserving an artwork.

## Non-Destructive Imaging Techniques

Over years, many different types of electromagnetic spectrum analyses have been adopted for use in art preservation, attribution, and cultural heritage conservation tasks. The specific spectrums used range from ultraviolet (UV), visible, near infrared (Near IR), shortwave infrared (SWIR), x-ray, and terahertz (THz). Multispectral and Hyperspectral image (MSI/HSI) analyses combine the use of different spectrums and allows for better analysis as "each material reflects, absorbs, and emits electromagnetic radiation according to its molecular composition and shape."[3] The multispectral/hyperspectral images can be acquired with frame cameras or scanning devices with single or linear arrays of sensors.

Figure 1 on page 6, Spectral Scanning Device being used on Rembrandt's *The Night Watch* painting, Rijksmuseum. Image used courtesy of Bridget A. Moorman.

**Figure 1** shows a scanning device being used on Rembrandt's *The Night Watch* painting at the Rijksmuseum. The basic physics of the non-destructive imaging technique relies upon how a material will absorb, reflect and/or transmit the frequency being projected onto the material. In **Figure 2** the sensors detect the reflectance spectra of each pixel that is scanned resulting in a file-cube which has the spatial coordinates (x,y) and one spectral coordinate (wavelength – $\lambda$).

**Figure 3** shows how the different wavelengths penetrate the different layers of a painting. By being able to visualize the layers underneath what is currently visible, conservationists can better date the artwork as well as detect any degradation due to aging, environment (where displayed or stored), and previous conservation efforts. As per the figure, THz penetrates to the preparation layer, while the IR, Visible, and UV investigate higher layers of the painting, with x-rays revealing the lower support layer.

Each of these spectra also have specific information they are better suited to acquire. The visible spectrum is used mainly to record the color and spatial information about the painting. The short-wave infrared region (SWIR – 1000-1700 nm) excels at highlighting underdrawings or pentimenti. This layer also can reveal underpaintings that have been covered over with the currently visible paint layer. Visible and near infrared (400-700 nm and 700-1000nm, respectively) are used for detection of surface defects, paint pigments, and cracks. This range also can detect "false colors" which in the visible spectrum may look the same, but in the IR spectrum have a different behavior.

As an example, this can indicate that a conservationist may have accurately depicted the correct visible color, but used a different set of substances in the paint to achieve the pigments. These surface and subsurface features can also reveal stylistic techniques of the artist. In the THz imaging range, conservationists are able to discern different surface layer preparation of the wood (or canvas) indicative of a specific school or art timeframe by comparing the different surface preparation techniques used in different times, such as medieval versus renaissance. This also helps with dating and attribution.[4,5,6,7,8,9]

## VISUAL-PHOTOGRAMMATIC FOR 3-D IMAGING AND RECONSTRUCTION

In a quasi-related approach to spectroscopy for 2-D art, a photogrammetric (visual) technique was used for 3-D imaging and reconstruction of historical monuments for virtual reality/museum purposes and historical information/preservation. In the photogrammetric approach, an immersive 3-D representation of the "Fontana Maggiore" in Perugia was created. 564 photographs were taken of the fountain at different perspectives with the same photo parameters: ISO sensitivity, focal length, exposure time, and aperture. In order to obtain a good 3-D visual model with this technique, there needs to be large overlaps (70%) between successive photographs. This allows for a stereoscopic set of data from which can be derived the 3-D model. The photos were then processed in a photogrammetry software to build the 3-D visual model. This photogrammetric technique was able to produce enough resolution such that an observer felt immersed in the scenario.[10]

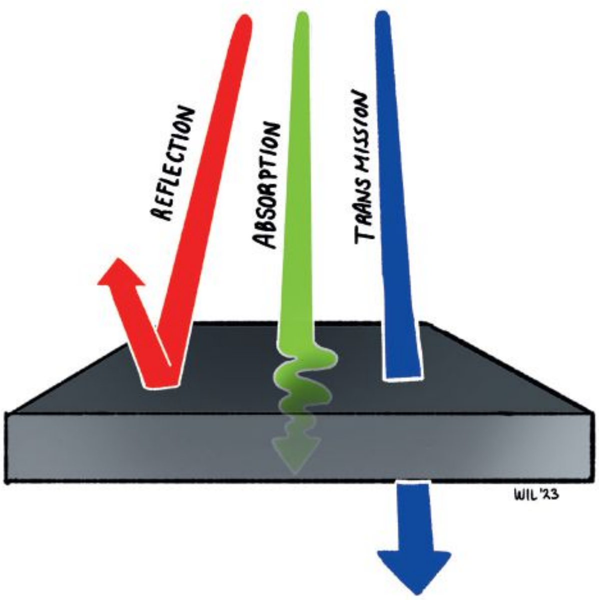


Figure 2. How material will reflect, absorb, and/or transmit non-destructive imaging frequencies/spectras. Image by Wilhelmina Hill-Bearhs.

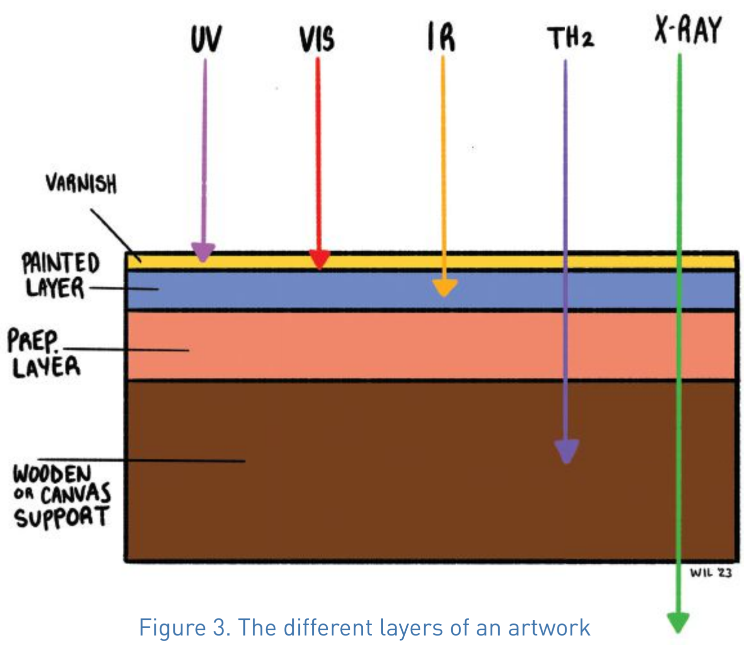


Figure 3. The different layers of an artwork penetrated by the different non-destructive imaging spectra techniques. Image by Wilhelmina Hill-Bearhs.

"By being able to visualize the layers underneath what is currently visible, conservationists can better date the artwork as well as detect any degradation due to aging, environment, and previous conservation efforts."

## ATTRIBUTION AND MACHINE LEARNING TECHNIQUES

The authentication and attribution of artwork is a precarious task, especially lately. In 2018, it was estimated that 20% of the paintings in UK museums were fakes.[11] Also, in 2018, one French museum found out that 50% of its artworks were fakes.[12] In 2012, the Metropolitan Museum of Art estimated that 40% of artworks on sale were fakes.[13] This has led to an increased desire to use more scientific and objective techniques for art attribution, with one of those techniques being the use of machine learning (ML) on digital datasets of artworks.

Authentication or attribution has traditionally relied upon a combination of "scientific analysis, connoisseurship, and provenance."[14] Scientific analysis can be fooled by forgers using materials from a particular age and copying the artists' styles. Provenance relies upon documentation of ownership over the years. Connoisseurship, which relies upon experts and expert associations to be able to examine artworks for authenticity, can at times become 'tunnel-visioned' possibly leading to inappropriate behavior limiting attribution to actual artworks to ensure scarcity and concomitant increase in market prices, or mis-attribution due to human error. ML and algorithms developed by the ML techniques have become the next tool in the artwork attribution arsenal; however, this technique is not without its faults either.

## MACHINE LEARNING EXAMPLES

The Department of Physics at Case Western Reserve University applied ML to "analyze topographical data obtained by optical profilometry." Surface topography "reveals unintended stylistic elements embedded in the surface of the painting that include deposition and drying of the paint, patterns in the brushwork, and physiological factors.[15]

The argument is that each artist has an unconscious 'fingerprint' attributable to their style of painting and that the brushstroke (weighting across the bristles and their flow across the canvas) and amount of paint (height of paint deposited on the canvas) used would be consistent with each artist regardless of other stylistic aspects of a painting or tools used. The unique physiological aspect could be attributed to the fine motor control of the artists' hand. They measured the surface height of each painting using a high resolution optical profilometer. They then used an ML technique of convolutional neural networks (CNN) to analyze the data. In order to avoid over-fitting of the model, they trained on a larger data set and then used the trained model to predict attribution on a smaller data set. The specific results were fairly accurate at 96.1% correct attribution. They also tested different sample size areas of the artwork for accuracy with their ML model. Their model exhibited a broad accuracy of 95% between sample sizes of 5-15 mm, which equated to between 100 and 300 pixels with their profilometry system. They also found that their model gave more accurate attribution predictions than similar ML techniques that use color metrologies versus surface height metrology.

Rutgers University and the Atelier for Restoration and Research of Paintings in the Netherlands collaborated on another application of ML techniques to determine attribution. Their premise was the 2-D strokes used by artists in drawings were unique to the artist: "the shape, tone, and relative length of the beginning, middle, and end of each stroke."[16] This stroke is the artist's 'unique unintentional signature' and is difficult to forge. They used 297 line drawings by Picasso, Matisse, Shiele, and Modigliani collected as digital images from various sources. They then commissioned five artists to make 83 drawings similar to those of the masters using the same techniques as a data set for only testing their algorithm. The masters' images and the drawing strokes were quantified and classified by studying the handcrafted features, which included the shape of each stroke and the boundary statistics, and learned representation features which covered the tone variation and local shape characteristics. The handcrafted feature data set was classified using a support vector machine (SVM), while the learned representation features were classified using a gated recurrent unit (GRU) a more complex version of a

Figure 4: On the right is the '*de Brecy Tondo*' painting, which depicts the central figures of the Renaissance master's famed *Sistine Madonna*. On the left are the two nearly identical central figures of the complete Sistine Madonna.

recurrent neural network (RNN). The training was done inter and intra-artist using both classification techniques (handcrafted and learned representation) described above. Then the fake drawings were run through the algorithm. The results showed that the handcrafted feature technique set approach rejected fake drawings with 100% accuracy, while the GRU-RNN learned representation feature technique performed poorly at detecting the fake drawings. Moreover, they were able to discriminate between different artists' drawings at the stroke level with high accuracy.

## MACHINE LEARNING AND THE TRAINING SET

In an example of competing ML claims, recently a painting was attributed to one artist using one set of ML techniques while another ML technique attributed the painting to another artist. In early 2023, a painting known as the *de Brecy Tondo Madonna* was attributed with 95% accuracy to Raphael using an ML and neural network technique at Bradford University, UK, that relied upon facial recognition.[17] Three weeks later, another ML company based in Switzerland, Art Recognition, announced that they had run the painting through their ML algorithms and their prediction with 85% accuracy was that the painting was not by Raphael (**See Figure 4 above**). Art Recognition requires 200 images from a specific artist to build and train their algorithm, and uses the whole painting, not a specific portion of it.[18]

The results above caused many in the art world to call for caution in the sole use of ML algorithms for attribution of artworks. The opposing results above demonstrate that the limitations of the algorithms and training sets should be understood and that the ML techniques should currently be an adjuvant to the other techniques used in cultural heritage conservation and attribution.[19]

## CONCLUSION

As with all other industries, the advent of computing and machine learning has changed the perspectives and tools used to assist in the creation, maintenance, and identification of the products in those industries. The tools used in cultural heritage conservation and attribution rely heavily upon the physical principles and engineering in the world: understanding of optics, the electromagnetic spectrum, machine learning processes and techniques, applied mathematics, data processing, and the equipment used to perform these tasks. These, combined with an understanding of art and the materials used in art, the different schools and techniques, and the different periods of art, can possibly make for a very interesting career in the creative work of art and cultural heritage conservation for an engineer.

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has 30+ years' experience in the clinical engineering/digital health field working and consulting for large healthcare organizations as well as serving as chair of the board of examiners for certification in clinical engineering (2011-13). She has worked in biomechanical research, power-line relay design and space system launch, and telecommunications. As an Air Force reservist, Bridget served as IMA to the MILSATCOM Directorate. Her B.S. from Arizona State University (ASU) is in ME; M.S. in BME from Rensselaer Hartford Graduate Center; and MAS in healthcare informatics ASU College of Health. Her professional awards include the 2019 ACCE/HIMSS Excellence in Clinical Engineering and Information Technology Synergies Award. She is an Instrument Private Pilot, Single Engine Land.

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