Case Western Reserve University

Department of Physics
Senior Project Proposal

Machine Learning to Match Paintings to their Artists Using Variation in Brushstroke Styles

November 18, 2019

Gundeep Singh

gxs372@case.edu

Advisor: Michael Hinczewski

1 Abstract:

The capability of automatically extracting brushstroke features from paintings has further advanced the possibilities of quantitatively analyzing artworks, which are especially needed in identifying the cases of art forgeries. In this work, we propose a deep Convolutional Neural Network (CNN) based algorithm that is capable of distinguishing between 4 similar paintings and identifying the corresponding artist who painted them. Our data consist of small tiles extracted from the paintings and magnitudes of vertical brushstroke heights at every 2D transverse location on the tiles. We hypothesize that a variation in the style and pattern of brushstroke can be used to 'teach' an AI algorithm to distinguish between our 4 artists. In the later part of this work, we will utilize the method of transfer learning to enhance our model's performance, as this technique provides the benefit of using other pretrained models to start the training from physically-relevant network parameter values instead of completely random values, and has proven extremely relevant in the cases when image availability is limited. The purpose of this project is thereby twofold - one, to develop an AI architecture that can potentially be utilized to separate 'real' art from its imitation. Second, to explore the performance of transfer learning using different pretrained datasets - other painting 2D image data (ArtUK) and other non-painting imageset (ImageNet).

2 Introduction

In 2014, a Geneva-based Fine Art Expert Institute (FAEI) reported that between 70 to 90 percent of the artwork that the institute analyzed turned out to be fake.[1] Similarly, in 2018, a small art museum called 'The Museé Terrus' in Elne, France, saw its collection cut by more than half when it was revealed that 82 of the museum's 142 works were forgeries. [2] Investigation into the cases of fake artwork or art forgeries currently require a combination of a variety of techniques including X-ray, infrared scan and carbon dating in order to scientifically separate fakes and forgeries from real artworks. Institutes like FAEI charge up to $1900 to verify the authenticity of paintings using a combination of aforementioned techniques. [3] In pursuit of lowering this cost and eliminating the labor-incentive methodologies involved, in this study, we propose a unique combination of 3D profilometry technique and Artificial Intelligence that lays the foundation for developing automated systems that are capable of distinguishing between real art and their imitations .

Non-contact 3D profilometry is a surface analysis technique that measures surface morphology of materials without touching the sample. Therefore, this technique has been prominent in measuring micro-scale height variation in the solid film of dried paint, while avoiding any shape alteration that may be caused by contact technologies. [4] In this study, we propose to develop a deep-learning algorithm that is capable of distinguishing between paintings by utilizing the data obtained from non-contact 3D profilometry scans of the paintings. To the extent of our knowledge, this will be the first time AI and profilometry will be used in combination to quantitatively analyze the surface features and patterns in paintings.

Along with implementing deep learning to match paintings with their corresponding artists, we also want to study how optimization of machine learning algorithms is correlated with physical and mathematical artifacts of the problem in hand. We first want to know if the optimal size of the small patches cropped from the paintings in the training dataset is a reflection of physical features like the brush width or the shapes in the paintings itself. We will then also implement the technique of transfer learning to improve the accuracy of our neural network and formulate the mathematical framework of how transfer learning fits into the optimization of machine learning parameters.

3 Specific Goals

The specific goals we want to achieve in this work are as follows:

- Implement deep learning to match patches obtained from 12 paintings (4 artists X 3 paintings each) to their corresponding artist
- Find optimal patch size and its correlation with physical aspects (including but not limited to brush width and the way objects are drawn in the painting)
- Implement transfer learning to improve test accuracy and performance using ImageNet and ArtUK datasets
- Formulate unsupervised learning algorithm that is capable of distinguishing between different painting patches based on the learned brushstroke variation threshold. This will be a potential foundational basis of the algorithmic method that can be applied to investigate cases of art forgeries and fake art.

4 Literature Review

The first publication that proposed the application of identifying characteristic stylistic patterns in solving the cases of art forgeries was published in 1968 by Theodore Rousseau. [5] Rousseau cited a case in which a forger used a chemical medium similar to Bakelite to make the painting appear centuries old in just a few hours, and thus became successful in escaping the identification of forgery through the X-ray method. [5] The forgery in this case was only identified much later when stylistic differences in the use of color palette were recognized by a team of art historians that included Rousseau. [5]

Artist-specific stylistic patterns can comprise of various factors that can be utilized to distinguish real art from its imitations. However, one factor that has contributed the most toward scientific generalization of style-identification methodology of paintings is the variation in artist-specific brushstroke techniques. [6] In 2013, Zang et al developed a mathematical algorithm to automatically extract stroke features from paintings and used them to characterize different stroke-related artistic styles. [7] Their main purpose was to lay out a foundation towards the development of style transfer algorithm using stroke-based artistic style characterization. However, this task was recently accomplished in 2015 by implementing an artificial intelligence system based on deep neural network. [8]

Deep learning-based neural networks have been remarkably successful in solving many related problems in both forensics ([9]) and analysis of artworks like painting ([10]). While classification of paintings based off of only height data has not been done to date, previous papers have shown that height characteristic data contain relevant information about extracting brushstroke styles, which has been proven to be a key parameter in many quantitative analysis of painting. [7] Transfer learning has also been successful in improving neural network performances, especially in cases when access to training data is limited. [11] However, a rigorous understanding of how transfer learning improves performances is still missing. In this study we will use two prominent datasets ImageNet [12] and ArtUK [13] to heuristically study the workings of transfer learning. ImageNet is a continually expanding training dataset of images obtained using different modalities that has been pretrained to identify 100,000 different categorical images. While, ArtUk is an open source database that is a collection of scans of various artistic samples, and they have been used to train different

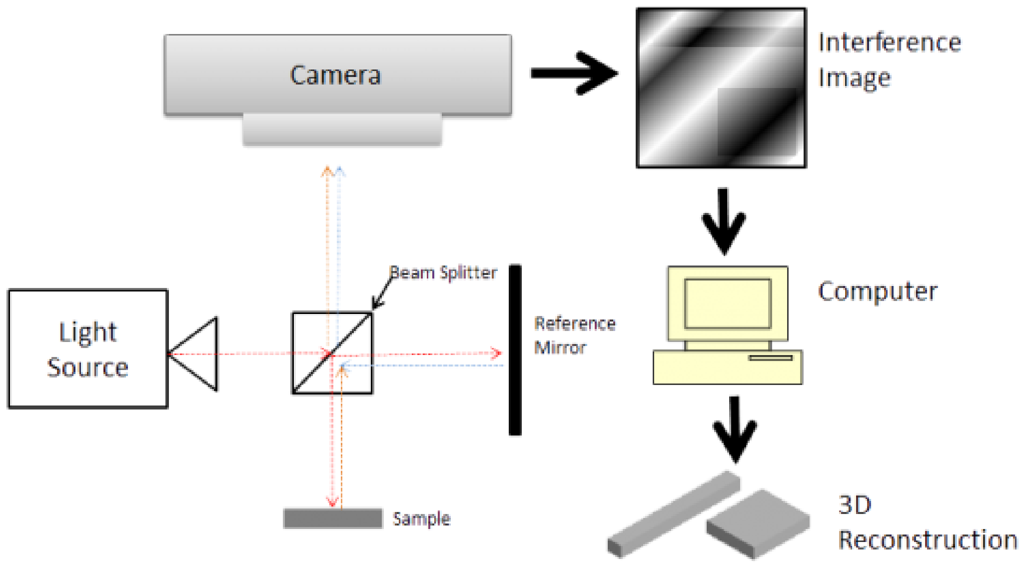

Figure 1: Schematic of Non-Contact 3D Profilometer: Visible light is shined on a beam splitter. One ray travels to a reflected mirror, while the other is reflected by a sample point with a certain roughness. When the 2 beams are collected at the detector, interference pattern is observed due to the path difference, which is then decoded to give 3D reconstruction of the surface of the sample.

models including OmniArt [13]. We will measure the improvement in network's performance using the 2 transfer learning networks to understand how does using a model that uses art-based data compares with a model that uses images of all different modalities.

5 Method

We asked 4 artists (1-4) from Cleveland Institute of Art to paint 3 similar paintings (a-c) in equivalent conditions, including availability of color palette, brush widths and canvas size. The twelve paintings were then scanned with a non-contact 3D profilometer. A schematic of the optical profilometer is shown in Fig. 1. (reproduced from [14]). As shown in this figure, the optical profilometry works by measuring the differences in the path length of two light beams - one that reflects off the surface with height h and the other that reflects off an almost completely reflective surface. The path difference generates an interference pattern, which is then converted to physical height values at different spatial points. Profilometry scans of images 1a, 2a, 3a, and 4a are shown in Fig 2. Each of the paintings is 3000 X 2400 pixel in size, where each px correspond to about 50 μm. The heights are shown to be centered around the mean.

As seen in Fig. 2, the height variation between images is not easily identified by naked eye. This can also be inferred from Fig 3, which shows the histogram plots of all 3 paintings combined for each of the 4 artists. However, by implementing Artificial Intelligence we expect to find small spatial patterns of brushstroke that are capable of distinguishing between the artists. We will first build a Simple Convolutional Neural Network (CNN) consisting of 3 layers of convolution and max-pooling operations. While the performance of this model will be far from ideal, we expect to gain

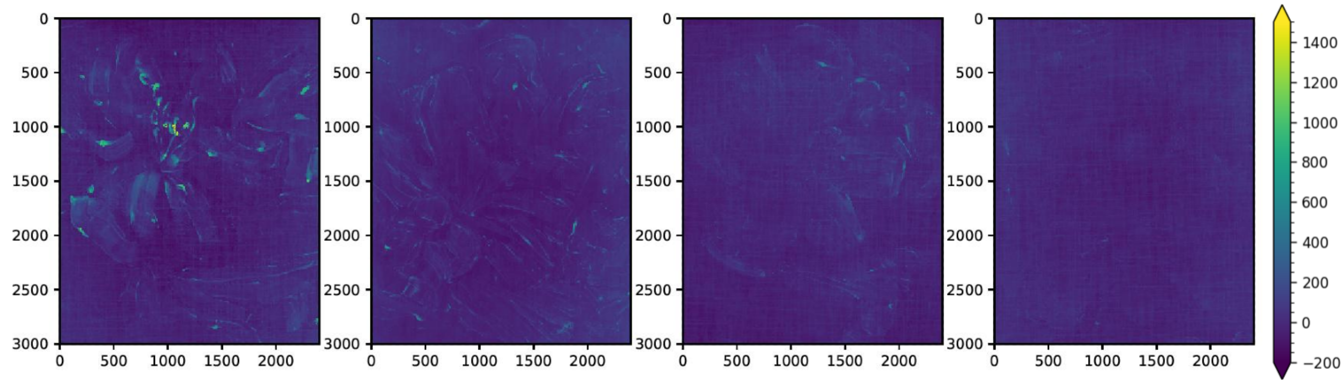

Figure 2: Height profilometry data shown for Images 1a, 2a, 3a, and 4a (L-R). The color bar shown on the right indicates the height values of the dried paint in micrometers.

important information required to finetune hyperparameters of the neural network. Next, we will build an architecture based on ResNet skip-connection-like structure. ResNet provides a building block for making pretrained networks that are frequently used in computer vision. [15] ResNet structure is particularly helpful in preventing the accuracy degradation of a deep neural network, as it only trains on residual incremental differences (hence the name ResNet) and does not incur loss of previous level abstractions. [15]

In the latter part of our study, we will revise our architecture to incorporate pretrained datasets to implement transfer learning using both feature extraction and fine-tuning techniques. Transfer learning, as the name suggests, is the improvement of learning in a new task by taking advantage of knowledge already learned in another 'related' task, which is then transferred (as learned weights and biases) to achieve a better performance. [16] By implementing transfer learning, we not only want to improve our accuracy of identifying correct painters, but we will also compare transfer learning from 2 different datasets, namely ImageNet and OmniNet, to understand the 'relatedness' of the two tasks needed to successfully 'transfer the learning'.

After accomplishing supervised learning tasks, we will tackle the problem of distinguishing brushstroke variation from a single data file using clustering methodology within unsupervised learning. The exact framework of the network architecture of unsupervised learning will depend on the success of supervised learning, as that will help us determine the unsupervised distance metric needed for identifying significant variation between parts of our dataset.[17]

6 Discussion

Patterns in brushstroke styles have previously been used to distinguish art paintings of famous artists like Vincent van Gogh from their contemporaries. [18] However, in this study we propose a methodology that combines optical profilometry and deep learning system to automatically match paintings to their corresponding student artists by using variation in the dried paint height values. By implementing deep learning and transfer learning, we also plan to heuristically study the physical basis of machine learning optimization for our data, specifically how different patch sizes and different pretrained models of different image datasets affect the learning of AI systems. The system we will develop as part of this project will not only have potential applications in the investigation of art forgery cases, but can also be extended to be used in building a style-based image retrieval system, differentiating art movement period, and even in building systems that regenerate learned

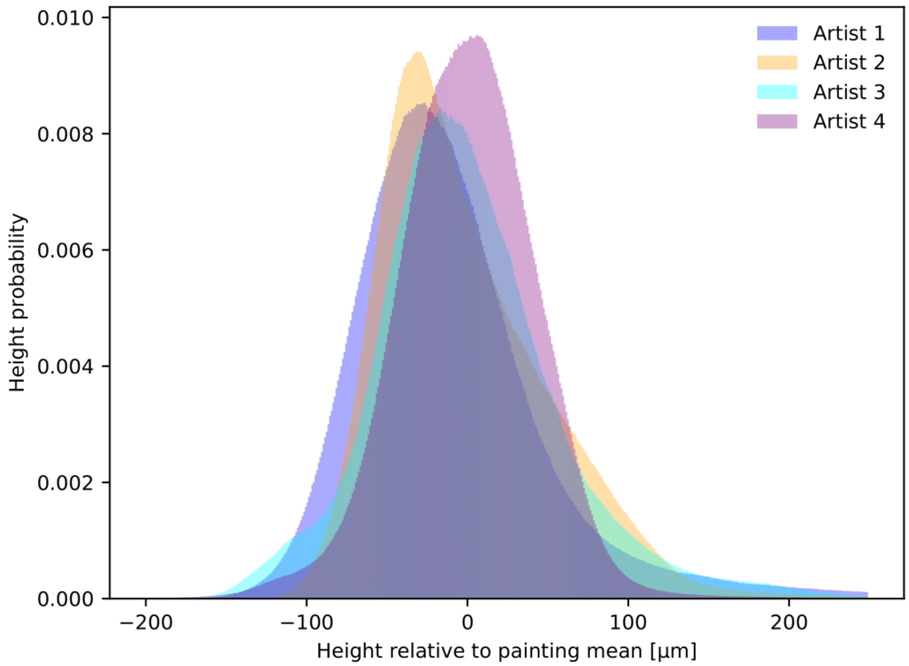

Figure 3: Histogram depicting the probability of occurring of each of the height measurement centered around the overall mean height. The three images are combined for each of the 4 artist and the histogram is obtained

forms of art.

References

[1] Larson N. Fine Arts Experts Institute: Lab sleuths in Geneva help art world uncover fakes, ND, ArtDaily, url: https://artdaily.cc/news/73562/Fine-Arts-Experts-Institute–Lab-sleuths-in-Geneva-help-art-world-uncover-fakes.

[2] Zachos E. How More Than Half the Art in This French Museum Was Forged, May 1, 2018, National Geographic, url: https://www.nationalgeographic.com/news/2018/05/fake-art-france-culture-spd/.

[3] Artnet News. (2014). Over 50 Percent of Art is Fake, October 13, 2014, Art and Law, url: https://news.artnet.com/market/over-50-percent-of-art-is-fake-130821.

[4] Li D. (2017) Automated Real-Time Evolution Monitoring of Drying Paint Morphology, Nanovea, url: https://nanovea.com/App-Notes/paint-drying-morphology.pdf.

[5] T. Rosseau. (1968). The stylistic detection of forgeries. In The Metropolitan Museum of Art Bulletin, volume 26, 6, pages 247–252. The Metropolitan Museum of Art.

[6] Mukundan R. Putri, T. and Neshatian K. (2017). Artistic Style Characterization of Vincent Van Gogh s Paintings using Extracted Features from Visible Brush Strokes. In ICPRAM (pp. 378-385).

[7] Huang H. Zang, Y. and C. Li. (2013). Stroke style analysis for painterly rendering. In Journal of Computer Science and Technology, volume 28, 5, pages 762–775. IEEE.

[8] A. Ecker L. Gatys and M. Bethge. (2015). A neural algorithm of artistic style. Nature Communications.

[9] Hofmann H. Tai X. H. Carriquiry, A. and S. VanderPlas. (2019), Machine learning in forensic applications. Significance, 16: 29-35.

[10] F. Yger Y.-K. Noh A. Lecoutre, B. Negrevergne and M.-L. Zhang. (2017).Recognizing Art Style Automatically in painting with deep learning, Proceedings of Machine Learning Research, vol. 77, pp. 327–342.

[11] L. Torrey and J. Shavlik. (2009). Transfer learning. IGI Global.

[12] R. Socher L.-J. Li K. Li J. Deng, W. Dong and L. Fei-Fei. (2009). ImageNet: A Large-Scale Hierarchical Image Database. IEEE Computer Vision and Pattern Recognition (CVPR).

[13] G. Strezoski and M. Worring. (2017). OmniArt : Multi-task deep learning for artistic data analysis . CoRR. arXiv:1708.00684.

[14] Nanoscience Instuments. Optical Profilometry, Nanoscience.com, url: https://www.nanoscience.com/techniques/optical-profilometry/.

[15] Shaoqing Ren Kaiming He, Xiangyu Zhang and Jian Sun. (2015) Deep residual learning for image recognition. CoRR, abs/1512.03385.

[16] Emilio Soria Olivas, Jose David Martin Guerrero, Marcelino Martinez Sober, Jose Rafael Magdalena Benedito, and Antonio Jose Serrano Lopez. *Chapter 11, Transfer Learning, Handbook Of Research On Machine Learning Applications and Trends: Algorithms, Methods and Techniques - 2 Volumes.* Information Science Reference - Imprint of: IGI Publishing, Hershey, PA, 2009.

[17] Dean P. Foster Abhishek A. Gupta and Lyle H. Ungar. Unsupervised Distance Metric Learning Using Predictability, June 2008.

[18] E. Hendriks J. Li, L. Yao and J. Z. Wang. (2012). Rhythmic brushstrokes distinguish van gogh from his contemporaries: Findings via automated brushstroke extraction. IEEE Trans. Pattern Anal. Mach. Intell.