Towards discovery of the artist's style: Learning to recognise artists by their artworks.

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***Abstract*—Author attribution through the recognition of visual characteristics is a commonly used approach by art experts. By studying a vast number of artworks, art experts acquire the ability to recognise the unique characteristics of artists. In this paper we present an approach that uses the same principles in order to discover the characteristic features that determine an artist's touch. By training a Convolutional Neural Network (PigeoNET) on a large collection of digitised artworks to perform the task of automatic artist attribution, the network is encouraged to discover artist-specific visual features. The trained network is shown to be capable of attributing previously unseen artworks to the actual artists with an accuracy of more than 70%. In addition, the trained network provides fine-grained information about the artist specific characteristics of spatial regions within the artworks. We demonstrate this ability by means of a single artwork that combines characteristics of two closely collaborating artists. PigeoNET generates a visualisation that indicates for each location on the artwork who is the most likely artist to have contributed to the visual characteristics at that location. We conclude that PigeoNET represents a fruitful approach for the future of computer supported examination of artworks.**

***Index Terms*—Author attribution, convolutional neural networks, visualisation**

I. Introduction

IDENTIFYING the artist of an artwork is a crucial step in establishing its value from a cultural, historical, and economic perspective. Typically, the attribution is performed by an experienced art expert with a longstanding reputation and an extensive knowledge of the features characteristic of the alleged artist and contemporaries.

Art experts acquire their knowledge by studying a vast number of artworks accompanied by descriptions of the relevant characteristics (features) [1]. For instance, the characteristic features of Vincent van Gogh during his later French period include the outlines painted around objects, complementary colours [2], and rhythmic brush strokes [3]. As Van Dantzig [4] claimed in the context of his *Pictology* approach, describing works by an artist in terms of visual features enables the attribution of works to artists (see also [5]).

The advent of computers and high-resolution digital reproductions of artworks gave rise to attempts to partially automate the attribution of artworks [6], [7], [8]. Given the appropriate visual features, machine learning algorithms may automatically attribute artworks to their artists. As was (and still is) common practice in traditional machine learning, feature engineering, i.e., finding or defining the appropriate features, is critical to the success of the automatic attribution task. Close cooperation with art historians and conservators facilitated the feature engineering for artist attribution, which led to promising results in the automatic attribution of artworks by van Gogh and his contemporaries [3], [6], [9], [10], highlighting the value of automatic approaches as a tool for art experts.

Despite the success of feature engineering, these early attempts were hampered by the difficulty to acquire explicit knowledge about all the features associated with the artists of artworks. Understandably, the explicit identification of characteristic features posed a challenge to art experts, because (as is true for most experts) their expertise is based on tacit knowledge which is difficult to verbalise [11]. By adopting a method capable of automatically recognising the characteristics that are known to be important for the task at hand, the tacit knowledge of art experts may be operationalised [12].

Feature learning is an alternative to feature engineering that learns features directly from the data [12]. Feature learning is much more data intensive than feature engineering, because it requires a large number of examples to discover the characteristic features. In recent years, feature learning has shown great promise by taking advantage of deep architectures, machine learning methods inspired by biological neural networks. A typical example of a deep architecture is a convolutional neural network, which, when combined with a powerful learning algorithm, is capable of discovering (visual) features. Convolutional neural networks outperform all existing learning algorithms on a variety of very challenging image classification tasks [13]. To our knowledge, convolutional neural networks have not yet been applied for automated artist attribution. The objective of this paper is to present a novel and transparent way of performing automatic artist attribution of artworks by means of convolutional neural networks.

The question may be raised if automatic artist attribution is possible at all, when using visual information only. It has been frequently argued by scholars working in the art domain that semantic or historical knowledge, as well as technical and analytical information are pivotal in the attribution of artworks. The feasibility of image-based automatic artist attribution is supported by biological studies. Pigeons [14] and honeybees [15] can be successfully trained to discriminate between artists, with pigeons correctly attributing an art work in 90% of the cases in a binary Monet-Picasso attribution task. This shows that a visual system without higher cognitive functions is capable of learning the visual characteristics present in artworks. While it is unlikely that a perfect result can be achieved without incorporating additional information, these findings do pave the way for an attribution approach that learns to recognise visual features from data rather than from prior

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knowledge.

In this paper, we present PigeoNET, a convolutional neural network corresponding to the AlexNET architecture described in [13] to which we added a visualisation component due to [16]. PigeoNET is applied to an artist attribution task by training it on artworks. As such, PigeoNET performs a task similar to the pigeons in [14], by performing artist attribution based solely on visual characteristics. This implies that, in addition to authorship, PigeoNET may also take visual characteristics into consideration that relate indirectly to the artist (e.g., the choice of materials or tools used by the artist) or that are completely unrelated to the artist (e.g., reproduction characteristics such as lighting and digitization procedure). To ensure that the visual characteristics on which the task is solved by PigeoNET make sense, human experts are needed to assess the relevance of the acquired mapping from images of artworks to artists. Our visualisation method allows for the visual assessment by experts of the characteristic regions of artworks.

In our artist attribution experiments, we consider three sources of variation in the training set and assess their effects on attribution performance: (1) heterogeneity versus homogeneity of classes (types of artworks), (2) number of artists, and (3) number of artworks per artist.

After training, the performance of PigeoNET will be assessed in two ways: (1) by determining how well it attributes previously unseen artworks, and (2) by generating visualisations that reveal artwork regions characteristic of the artist, or in case of artworks that are likely created by two or more artists, generating visualisation that reveal which regions belong to which artist, and could aid in answering outstanding art historical questions.

The remainder of the paper is organised as follows. In Section II we describe the PigeoNET model. In Section III the experimental setup is outlined and the results of the artist attribution task are presented. In Section IV we explore the features acquired by PigeoNET by visualising authorship for specific artworks. We discuss the implications of feature learning for the interdisciplinary domain of automatic artist attribution in Section V. Finally, Section VI concludes by stating that PigeoNET represents a fruitful approach for the future of computer-supported examination of artworks, capable of attributing artists to unseen artworks and generating visualisations of the authorship per region of an artwork.

II. PigeoNET

A convolutional neural network can learn to recognise the visually characteristic features of an artist by adapting filters to respond to the presence of these features in an image [17]. The filters are adapted to respond to a feature by adjusting the parameters, or weights, of the filters until a suitable configuration is found. The proper weights for this configuration are obtained by means of a learning algorithm called backpropagation [18], which requires no prior knowledge, other than the input images and some label (e.g., the artist who created it). In the case of artist attribution, the network will learn to recognise features that are regarded as characteristic of a certain artist, allowing us to discover these characteristics. PigeoNET is a convolutional neural network designed to learn the characteristics of artists and their artworks, so as to recognise and identify their authorship.

The filters in a convolutional neural network are grouped into layers, where the first layer is directly applied to images, and subsequent layers to the responses generated by previous layers. By stacking layers to create a multilayer architecture the filters can respond to increasingly complex features with each subsequent layer. The filters in the initial layers respond to low level visual patterns, akin to Gabor filters [19], whereas the final layers of filters respond to visual characteristic features specific to artists.

Because convolution is used to apply the filters to an image, or the response of a previous layer, the layers of filters are referred to as convolutional layers. The advantage of a convolutional layer, over a traditional neural network layer, is that the weights are shared, allowing the adaptive filters to respond to characteristic features irrespective of their position or location in the input [18]. In order to learn a mapping from the filter responses to a certain artist the convolutional layers are, typically, followed by a number of fully-connected layers which translate the presence and intensity of the filter responses to a single certainty score per artist. The certainty score for an artist is high whenever the responses for filters corresponding to that artist are strong, conversely, the certainty score is low when the filter responses are weak or nonexistent. Thus, an unseen artwork can be attributed to an artist for whom the certainty score is the highest.

A. *Visualisation of artist-characteristic regions*

While PigeoNET's attribution of an artwork is based on the entire artwork, regions containing visual elements characteristic for an artist are assigned more weight than others to achieve a correct attribution [20]. In order to increase our understanding of the attribution performed by PigeoNET, we aim to visualise such artist-characteristic regions. Several methods have been proposed for visualising trained convolutional neural networks [16], [21] and other layered algorithms [22]. We adopt the occlusion sensitivity testing method proposed by [16] for obtaining visualisations of artist-characteristic regions, which can be considered a weakly supervised localisation method. By systematically occluding a small image region of an artwork, the importance of the occluded region is determined by observing the change in the certainty score for the correct artist. When an occluded region is very important (or highly characteristic) for correctly identifying the artist, there will be a significant drop in the certainty score generated by PigeoNET. Inversely, occluding a region that is atypical for the correct artist will result in an increase in the certainty score. A region for which occlusion results in a drop of the certainty score is considered characteristic for the artist under consideration. This approach to creating visualisations allows us to show the approximate areas of an artwork which are representative of an artist.

As an illustration, Figure 1 depicts *The feast of Achelous* by Peter Paul Rubens and Jan Brueghel. It is an artwork created

Fig. 1. "Peter Paul Rubens and Jan Brueghel the Elder: The Feast of Achelous" (45.141) In Heilbrunn Timeline of Art History. New York: The Metropolitan Museum of Art, 2000–. http://www.metmuseum.org/toah/works-of-art/45.141. (October 2006)

by two artists; Rubens painted the persons and Brueghel the scenery [23]. Although there is no single correct artist, the certainty score for Brueghel would decrease if the scenery were to be occluded, whereas the certainty score for Rubens would drop if the figures were occluded. Even when only part of the figures or part of the scenery were to be occluded, we would see a drop in confidence scores. In a similar vein, when even smaller regions of the painting have been occluded, it becomes possible to identify important regions on a much more detailed scale.

III. Author attribution experiment

The goal of an artist attribution task is to attribute an unseen artwork to the artist who created it. To be able to perform this task adequately, PigeoNET needs to discover features that distinguish an artist from other artists, but especially to discover features that are characteristic of each artist. In the rest of this section we will discuss the dataset, network architecture, training procedure, evaluation procedure, and the results.

A. Experimental setup

1) Dataset: The characteristic features of an artist can be discovered by studying artworks which are representative of that artist. Yet, obtaining a sufficiently large sample of such images is problematic, given the lack of (automatic) methods and criteria to determine whether an artwork is representative. A commonly taken approach to circumvent the need for a representative sample is to take a very large sample. As such, a dataset that contains a large number of images, and a large number of images per artist, is required.

The Rijksmuseum Challenge dataset [24] consists of $112,039$ digital photographic reproductions of artworks by $6,629$ artists exhibited in the Rijksmuseum in Amsterdam, the Netherlands. All artworks were digitised under controlled settings. Within the set there are $1,824$ different types of artworks and 406 annotated materials, such as paper, canvas, porcelain, iron, and wood. To our knowledge, this is the largest available image dataset of artworks, and the only dataset that meets our requirements.

We divided the Rijksmuseum Challenge dataset into a training, validation, and test set (cf. [24]). In this paper these sets are used to train PigeoNET, to optimise the hyper-parameters, and to evaluate the performance of PigeoNET on unseen examples, respectively. The dataset contains a number of artworks which lack a clear attribution, these are labeled as either 'Anonymous' or 'Unknown'. We chose to exclude these artworks, because our objective is to relate visual features to specific artists.

Whilst the Rijksmuseum Challenge dataset contains a large number of images of many different types of artworks by a large number of artists, there are many artists for whom only a few artworks are available or artists who have created many different types of artworks. As stated in the Introduction, these variations might influence the performance of PigeoNET in non-obvious ways. To this end we consider the following three sources of variation: (1) heterogeneity versus homogeneity of classes (types of artworks), (2) number of artists, and (3) number of artworks per artist.

Two main types of subsets were defined to asses the effect of heterogeneity versus homogeneity of artworks: type A (for "All") and type P (for "Prints"), respectively. As is evident from Table II, prints form the majority of artworks in the Rijksmuseum Challenge dataset. The homogeneous type of subsets (P) has three forms: P1, P2 and P3. Subsets of type P1 have varying numbers of artists and artworks per artist (as is the case for A). Subsets of type P2 have a fixed number of artworks per artist. Finally, subsets of type P3 have a fixed number of artists. We remark that the number of examples per artist for the subsets in A and P1 are minimum values. For very productive artists these subsets may include more artworks. For subsets of types P2 and P3, the number of examples is exact and constitutes a random sample of the available works per artist. A detailed overview of the resulting 15 subsets is listed in Table I. For the heterogeneous subset of at least 256 artworks of type A, Table II[1] provides a more detailed listing which specifies the three most prominent categories: Prints, Drawings, and Other. The Other category includes a variety of different artwork types, including 35 paintings.

All images were down-sampled to 256×256 pixels following the procedure described in [13], to adhere to the fixed input size requirement of the network architecture, and are normalised at runtime by subtracting the mean image as calculated on the training set.

2) Architecture: The architecture of PigeoNET is based on the Caffe [25] implementation[2] of the network described in [13], and consists of 5 convolutional layers and 3 fully connected layers. The number of output nodes of the last fully-connected layer is equal to the number of artists in the dataset, ranging from 958 to 26 artists.

3) Training: An effective training procedure was used (cf. [13]), in that the learning rate, momentum, and weight decay

[1] The largest subsets for P2 and P3 are identical, but are reported twice for clarity.

[2] Available at: http://caffe.berkeleyvision.org/model_zoo.html.

TABLE I
OVERVIEW OF SUBSETS AND THE NUMBER OF TRAINING, VALIDATION, AND TEST IMAGES PER SUBSET. THE SUBSETS ARE LABELLED BY THEIR TYPES. TYPE A ("ALL") ARE SUBSETS CONTAINING VARYING ARTWORKS, EXAMPLES AND EXAMPLES PER ARTIST. TYPE P ("PRINTS") REFERS TO SUBSETS OF PRINTS ONLY. P1: VARYING NUMBERS OF ARTWORKS, EXAMPLES AND EXAMPLES PER ARTIST. P2: NUMBER OF EXAMPLES CONSTANT (128). P3: NUMBER OF ARTISTS CONSTANT (78). FOR A AND P1, THE NUMBERS OF EXAMPLES PER ARTISTS REPRESENT THE MINIMUM NUMBERS, WHILE FOR P2 AND P3, THESE NUMBERS REPRESENT THE EXACT NUMBER OF ARTWORKS PER ARTIST.

Subsets	# Examples per artist	# Artists (classes)	# Training images	# Validation images	# Test images
A	10	958	56,024	7,915	15,860
	64	197	37,549	5,323	10,699
	128	97	28,336	4,063	8,058
	256	34	17,029	2,489	4,838
P1	10	673	44,539	6,259	12,613
	64	165	31,655	4,484	8,983
	128	78	23,750	3,408	6,761
	256	29	14,734	2,171	4,200
P2	128	26	3,328	1,209	2,277
	128	39	4,992	1,521	2,970
	128	52	6,656	2,160	4,341
	128	78	9,984	3,408	6,761
P3	10	78	780	3,408	6,761
	64	78	4,992	3,408	6,761
	128	78	9,984	3,408	6,761

TABLE II
LIST OF THE 34 ARTISTS WITH AT LEAST 256 ARTWORKS AND THE DISTRIBUTION OF ARTWORKS OVER MAIN TYPES (PRINTS, DRAWINGS, AND OTHER).

#	Name	Prints	Drawings	Other
1	Heinrich Aldegrever	347	27	
2	Ernst Willem Jan Bagelaar	400	27	
3	Boëtius Adamsz. Bolswert	592		
4	Schelte Adamsz. Bolswert	398		
5	Anthonie Van Den Bos	531	3	
6	Nicolaes De Bruyn	515	2	
7	Jacques Callot	1,008	4	1
8	Adriaen Collaert	648	1	
9	Albrecht Dürer	480	9	2
10	Simon Fokke	1,177	90	
11	Jacob Folkema	437	4	3
12	Simon Frisius	396		
13	Cornelis Galle (i)	421		
14	Philips Galle	838		
15	Jacob De Gheyn (ii)	808	75	10
16	Hendrick Goltzius	763	43	4
17	Frans Hogenberg	636		4
18	Romeyn De Hooghe	1,109	5	5
19	Jacob Houbraken	1,105	42	1
20	Pieter De Jode (ii)	409	1	
21	Jean Lepautre	559		1
22	Caspar Luyken	359	18	
23	Jan Luyken	1,895	33	
24	Jacob Ernst Marcus	372	23	2
25	Jacob Matham	546	4	
26	Meissener Porzellan Manufaktur			1,003
27	Pieter Nolpe	344	2	
28	Crispijn Van De Passe (i)	841	15	
29	Jan Caspar Philips	401	17	
30	Bernard Picart	1,369	132	3
31	Marcantonio Raimondi	448	2	
32	Rembrandt Harmensz. Van Rijn	1,236	119	29
33	Johann Sadeler (i)	578	1	
34	Reinier Vinkeles	573	50	

hyperparameters were assigned the values of 10^{-2}, 0.9, and $5 \cdot 10^{-4}$. The learning rate was decreased by a factor 10 whenever the error on the validation set stopped decreasing. The data augmentation procedure consisted of random crops and horizontal reflections. While orientation is an important feature to detect authorship the horizontal reflections were used to create a larger sample size, as it effectively doubles the amount of available training data, providing PigeoNET with sufficient data to learn from, while possibly negatively impacting PigeoNET's ability to pick up on orientation clues to perform classification. In contrast to [13], only a single crop per image was used during training, with crops of size 227×227 pixels, and the batch size was set to 256 images per batch.

All training was performed using the Caffe framework [25] on a NVIDIA Tesla K20m card and took between several hours and several days, depending on the size of the subset.

4) Evaluation: The objective of the artist attribution task is to identify the correct artist for each unseen artwork in the test set. To this end the performance is measured using the mean class accuracy (MCA), which is the average of the accuracies for all artists. This makes sure that the overall performance is not heavily biased by the performance on a single artist.

During testing the final prediction is averaged over the output of the final softmax layer of the network for 10 crops per image. These crops are the four corner patches and the central patch plus their horizontal reflections.

B. Results

The results of the artist attribution task are listed in Table III. The results on the artist attribution task show that the three sources of variation, (heterogeneity versus homogeneity of classes (types of artworks), number of artists, and number of artworks per artist.) affect the performance in different ways. The effect of heterogeneity versus homogeneity can be assessed by comparing the results for A and P1. The results obtained with P1 are slightly better than those obtained with A (except for 128 examples per artist). However, A and P1 differ also in number of artists which is likely to affect the performances as is evident from the results on P2 and P3.

The total number of artists (P2) and the number of examples per artist (P3) have a more prominent effect on the attribution performance of PigeoNET. Increasing the number of artists while keeping the number of examples per artist constant (as in P2) leads to a decrease in performance. With more examples per artist (P3) the performance increases tremendously.

Our results suggest that the effects of the number of artists and the number of examples per artist are closely related. This agrees with the findings reported in [13] and leads to the observation that by considering more examples per artist the number of artists to be modeled can be increased.

The subsets of type A are comparable to the subsets used in [24], who obtain a comparable MCA of 76.3 on a dataset containing 100 artists using SIFT features, Fisher vectors, and 1-vs-Rest classification.

Figure 2 shows a visualisation of the confusion matrix for the subset with at least 256 examples of all artwork types. The rows and columns correspond to the artists in Table II. The rows represent the artist estimates by PigeoNET,

TABLE III

MEAN CLASS ACCURACIES (MCA) FOR THE ARTIST ATTRIBUTION TASK ON THE 15 DATA SUBSETS. BOLD VALUES INDICATE THE BEST RESULT PER TYPE, THE OVERALL BEST RESULT IS UNDERLINED.

Subsets	# Examples per artist	# Artists (classes)	MCA
A	10	958	52.5
	64	197	68.2
	128	97	74.5
	256	34	**78.3**
P1	10	673	60.0
	64	165	70.2
	128	78	73.3
	256	29	**78.8**
P2	128	26	**63.9**
	128	39	55.6
	128	52	52.7
	128	78	52.0
P3	10	78	13.1
	64	78	38.0
	128	78	**52.0**

the columns the actual artists. The diagonal entries represent correct attributions which are colour coded.

Upon further analysis of the results for the 256 example subset (A) of all artwork types it can be observed that the best artist-specific classification accuracy (97.5%) is obtained for Meissener Porzellan Manufaktur, a German porcelain manufacturer (class 26). Among the different types of artworks in the dataset, these porcelain artworks are visually the most distinctive. Given that the visual characteristics of porcelain differ considerably from all other artworks in the dataset, it is not surprising that the highest classification accuracy is achieved for this class.

The worst artist-specific classification accuracy (60.6%) is achieved for Schelte Bolswert (class 4), as indicated by the yellow square on the diagonal in the confusion matrix (fourth row from below, fourth column from left). The low accuracy may be partially explained by the confusion between Schelte Bolswert and his older brother and instructor Boëtius Bolswert (class 3). Yet, because the classification accuracy for Boëtius Bolswert (86.3) seems much less affected by the confusion, an alternative possibility is that PigeoNET is more inclined to assign visual characteristics that are present in their works to Boëtius Bolswert because his works appear more frequently in the dataset.

In a similar vein, the misclassifications that occur between Fokke Simon (10) and Jan Caspar Philips (29), and between Jan Luyken (23) and Caspar Luyken (22) are notable. Fokke Simon was a student of Jan Caspar Philips, and Jan and Caspar Luyken were father and son. Both pairs of artists have worked together on several artworks in the Rijksmuseum Challenge dataset, despite the label in the dataset indicating that these artworks belong to only one of these artists. We became aware of these potential dual-authorship cases after having performed our main experiment. Dual-authorship cases will be examined in more detail through visualisations in Section IV.

C. *Visualisation and assessment*

Visualisations of the importance of each region in an artwork can be generated using the regions of importance de-

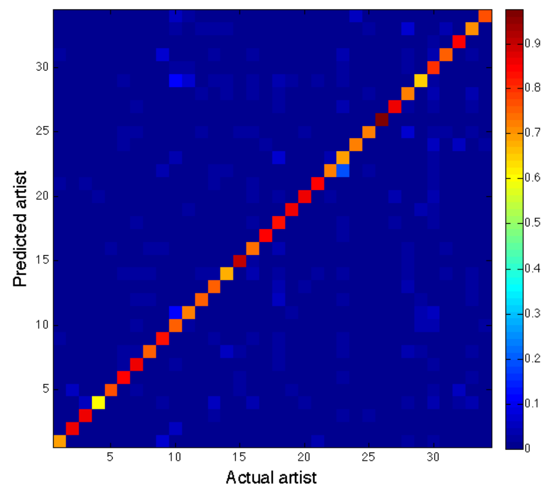


Fig. 2. Confusion matrix for all artists with at least 256 training examples of all artwork types. The rows represent the artist estimates and the columns the actual artists. Row and column numbers (from left to right and from bottom to top) correspond to those as listed in Table II.

tection method described in Section II-A, where the occlusions are performed with a grey block of 8×8 pixels, to indicate approximate regions which are characteristic of the artist. The regions of importance can be visualised using heatmap colour coding, as shown in Figure 3(b). The value of a region in the heatmap corresponds to the certainty score of PigeoNET for the artwork with that region occluded. In other words, a region with a lower value is of greater importance in correctly attributing the artwork, with (dark) red regions being highly characteristic of the artist, and (dark) blue regions being the least characteristic.

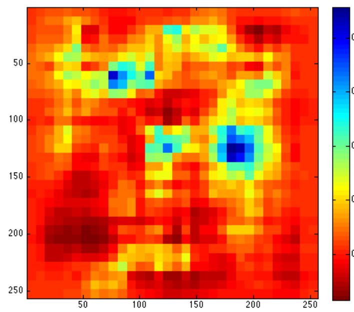
When comparing the artwork and heatmap in Figure 3 of the drawing by Rembrandt, it is very noticeable that PigeoNET assigns much weight to seemingly empty areas. The texture of the material on which an artwork is created can be indicative of the artist who created the artwork [26]. When taking a closer look at Figure 4, with enhanced contrast, it becomes apparent that the areas are not empty and that a distinctive visual texture is present. The visual pattern is sufficiently distinctive and artist-specific for PigeoNET to assign it a larger weight. The pattern is an example of a visual characteristic which is indirectly related to the artist. It illustrates the importance of the transparency of automatic attribution to allow human experts to interpret and evaluate the visual characteristic.

IV. DECIDING BETWEEN TWO ARTISTS

In the previous section we used PigeoNET to attribute an artwork to a single artist. Yet, as illustrated by the work of Peter Paul Rubens and Jan Brueghel in Figure 1, in many cases two (or more) artists have worked on the same artwork (see also [27]).

As evident from our results, PigeoNET had difficulty in correctly attributing artworks of closely collaborating artists. An intriguing explanation for PigeoNET's failure to assign the 'correct one' of two potential artists to artworks is that the artworks are created by both artists. In that case, it would not be a failure at all and indicates that PigeoNET discovered that

(a) Art work



(b) Heatmap

Fig. 3. Image (a) and heatmap (b) of *'Studie van een op de rug geziene man'* by Rembrandt Harmensz. van Rijn (1629-1630). Lower (red) values in the heatmap correspond to greater importance in correctly identifying Rembrandt.

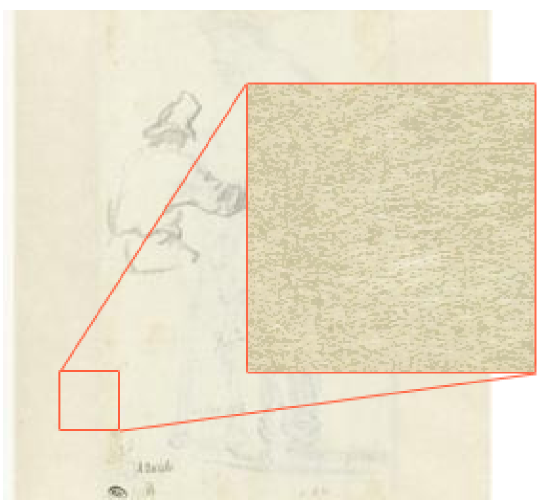


Fig. 4. Contrast enhanced detail view of a highly textured region of the artwork shown in Figure 3(a).

the two artists are similar, and it recognises the characteristic features of both artists, even if the work is attributed to only one artist. In the remainder of this section we demonstrate the possibility of using PigeoNET to perform a fine-grained analysis of an artwork, attributing individual image regions to an artist.

A. Discovering dual authorship

PigeoNET had difficulty in distinguishing between the works of Jan and Caspar Luyken, father and son who worked together and created many prints. Throughout their careers Jan Luyken chose to depict pious and biblical subjects, whereas Caspar Luyken mostly depicted worldly scenes [28]. As an example, we consider the artwork shown in Figure 5, *Over dracht der Nederlande, aan de Infante Isabella*. The work depicts the transfer of the Spanish Netherlands by Filips II to Isabella Clara Eugenia. Although, arguably it is a very worldly scene, it is nevertheless attributed to Jan Luyken. Could it be possible that the artwork is incorrectly attributed to Jan Luyken? Obviously, this is a question that has to be answered by experts of their works.

Fig. 5. Image of the *Over dracht der Nederlande, aan de Infante Isabella* by Jan Luyken, 1697 - 1699.

Our findings may support them in their assessment. Although, PigeoNET correctly attributed the artwork to Jan Luyken, the reported certainty score for Caspar Luyken is very high. Apparently, PigeoNET responds to visual features that are characteristic of Caspar Luyken. Using PigeoNET's visualisation, we are able to determine for each region how characteristic it is for each of the two artists. We created a visualisation based on the certainty scores for Jan Luyken and Caspar Luyken. Figure 6 shows the visualisation using color coding on a yellow to blue scale. The yellow regions are characteristic for Jan Luyken, whereas the blue regions are characteristic for Caspar Luyken, the green regions are indeterminate and show characteristics of either artists in equal amounts.

This example demonstrates the potential use of PigeoNET to support the study of dual authorship artworks.

V. DISCUSSION

Previous work on automatic artist attribution has shown that prior knowledge can be leveraged in order to engineer features for automatic artist attribution. In this paper, we presented a novel approach that does not rely on prior knowledge, and is capable of discovering characteristic features automatically enabling a successful artist attribution. Additionally, we demonstrated that PigeoNET visualisations reveal artwork regions most characteristic of the artist and that PigeoNET can aid in answering outstanding questions regarding dual-authorship.

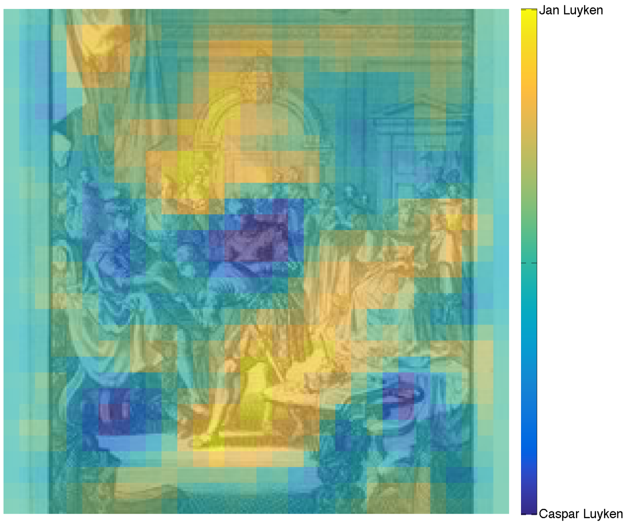


Fig. 6. Visualisation of how characteristic each image region is for the artists Jan and Caspar Luyken. The yellow regions are characteristic of Jan Luyken, whereas the blue regions are characteristic of Caspar Luyken.

In what follows, we discuss considerations regarding the dataset used and address how the selection of subsets may affect the nature of visual characteristics discovered.

Although the Rijksmuseum challenge dataset is the largest available dataset containing digital reproductions of artworks acquired under controlled conditions [24], it does suffer from two main limitations. First, given the wide variety of artwork types, it is unclear how the "controlled conditions" were defined for different artworks. Any variation in the reproduction setting (e.g., illumination, perspective, camera type) may be picked up by PigeoNET. Presumably, our P (prints only) datasets suffer less from this problem. Still, even in these datasets subtle differences in digitization may leave visual marks that are picked up by PigeoNET. An ideal dataset for attribution would be one in which no such visual marks are present. Unfortunately, such datasets do not exist and are hard (if not impossible) to create on this scale. Therefore, transparency of the acquired features by PigeoNET and proper visualisations are essential to aid art experts in their assessment of the feasibility of classifications.

The second limitation concerns the labeling of artworks. After having performed our main experiments, we discovered that for some artworks, the Rijksmuseum catalog lists multiple contributions, whereas the Rijksmuseum challenge dataset only lists a single artist [24]. The contributions listed in the Rijksmuseum catalog vary greatly (from inspiration to dual-authorship) and do not always influence the actual attribution, but do create uncertainty about the attribution of artworks in the Rijksmuseum challenge dataset. Although this significantly limits the possibility of learning stylistic features from such artworks, it does not prohibit PigeoNET from learning visual characteristics that are associated with the primary artist as such characteristics remain present in the artwork. Still, the validity and consistency of attributions is of major concern to safeguard the validity of methods such as PigeoNET. Also in the creation of such databases, involvement of human art experts is required.

The results obtained in this work on the automatic artist attribution task show that PigeoNET is capable of accurately attributing unseen works to the correct artist. The increase of performance for the sets with a higher number of examples shows that including more examples per artist leads to a better performance. Moreover, the complete Rijksmuseum Challenge dataset is a highly diverse dataset with many different types of art. For some cases (e.g., the porcelain of the Meissener Porzellan Manufaktur) this results in a class that is visually very distinctive from the rest of the dataset, which could make it easier to identify the correct artist. However, when comparing the performances obtained on the homogeneous P1 subsets (prints only) with those on the more heterogeneous A subsets (all artwork types), the difference in performance is quite small. This demonstrates that PigeoNET is capable of learning a rich representation of multiple artwork types without a major impact on its predictive power. Part of the types of features discovered in the A subsets are likely to distinguish between art types (e.g., a porcelain object versus a painting), rather than between author styles. In the P subsets, features will be more tuned to stylistic differences, because these subsets are confined to a single type of artwork.

Our findings indicate that the number of artists and the number of examples per artist have a very strong influence on the performance, which suggests that a further improvement of the performance is possible by expanding the dataset. In future research we will determine to what extent this is the case.

VI. Conclusion

In this paper we have evaluated a feature learning system to assess to what extent it is possible to discover an artist's visually characteristic features. The results on the automatic attribution task demonstrate that the system is capable, up to a high degree of accuracy, of using visual characteristics to assign unseen artworks to the correct artist. Moreover, we demonstrated the possibility of using the visual characteristics to reveal the artist of a specific region within an artwork, which in the case of multiple artists could lead to new discoveries about the origin and creation of important works of cultural heritage. Therefore, we conclude that PigeoNET represents a fruitful approach for future computer-supported examination of artworks.

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