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ROBUSTNESS OF DIGITAL ARTIST AUTHENTICATION

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Abstract. In many cases it is possible to determine the authenticity of a painting from digital reproductions of the paintings; this has been demonstrated for a variety of artists and with different approaches. Common to all these methods in digital artist authentication is that the *potential* of the method is in focus, while the robustness has not been considered, i.e. the degree to which the data collection process influences the decision of the method. However, in order for an authentication method to be successful in practice, it needs to be robust to plausible error sources from the data collection.

In this paper we investigate the robustness of the newly proposed authenticity method introduced by the authors based on second generation multiresolution analysis. This is done by modelling a number of realistic factors that can occur in the data collection.

1. Introduction

In recent years there has been a growing interest in detecting fake paintings by analyzing digital reproductions of the paintings. Different approaches are presented in [7, 2, 9, 5] and in [6] we present yet another method. It is a commonly accepted theory that the brushstrokes of an artist are unique [1] and the articles listed above try to capture and model the brushstrokes contained in the painting of the images.

Despite the individual successes in the above mentioned papers, one should be careful to interpret the results as though we have a general method for detecting forgeries. Especially the article [9] should give rise to extra thought when declaring victory from a novel approach; in this article it is concluded that the camera used to photograph the paintings can heavily influence the classification due to differences in the digitization.

Thus when testing a forgery detection method one should not ignore the origin of the data. This is also important because we do not (yet) have a standard for digital representation of visual art, since we do not yet know the optimal way of acquiring digital images that captures the parts relevant for detecting artistic differences.

When presenting our method in [6] we demonstrated that it was robust against changing cameras, meaning that we can classify images photographed by one camera based on images photographed with another camera.

In the present work we look further into the robustness of our method. Along the way we discuss a number of reasonable factors in the data acquisition that could influence the classification methods.

The motivation for our work has been the following questions:

Key words and phrases. Artist authentication, contourlet transform, hidden Markov models, classification.

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(1) How robust is our method to data collection?
(2) Which error sources (if any) influence the decisions of our method significantly?
(3) Can we digitally correct the errors introduced from the data collection?

A classification method is of limited interest if it necessary that the digital images have been obtained with exactly the same equipment under identical circumstances. If the data acquisition is too complicated and expensive, then the authentication might as well be performed manually. Hence, we should allow for some fluctuations in photographic equipment, quality and operator skill.

To our knowledge, the effects of image quality and acquisition have not been studied in the context of digital artist classification. We believe, however, that including considerations of this kind is a necessary part of testing the usefulness of the classification method.

In this work we have studied two significant groups of error sources (factors) that it is likely to encounter when photographing paintings, namely position of the camera relative to the painting and properties related to the camera.

Let us elaborate on the factors we have chosen and the motivation for considering them.

We think it is a reasonable assumption that a photographer should be willing to use a tripod when photographing the painting in question, hence ensuring that photograph is not blurred due to camera motion. However, it can be difficult to ensure that the camera and painting are perfectly aligned – touching a valuable painting is usually not an option and often the painting is tilted slightly from the wall. This has led us to consider the influence of the first two factors.

① Rotation of the camera compared to the painting.
② Keystone effect.

The camera may be rotated compared to the paintings and our method is not a priori rotation invariant.

The keystone effect is present if the camera is not parallel to the painting. If we have keystone effects straight lines in the painting remain straight, but parallel lines do not remain parallel.

Different cameras digitize images differently; as mentioned above, we demonstrated in [6] that our method is robust to this.

There are, however, a number of other factors related to the recording, that we find interesting to investigate. Specifically we have decided to look at the following factors.

③ Distortion by the lens.
④ Exposure.
⑤ Sharpening the picture digitally.
⑥ Contrast in the picture.

Virtually all lenses introduce some amount of distortion and the distortion is greater further from the center of the image, making the edges of the images more distorted. The distortion makes straight lines seem curved – if the lines curve away from the center we have barrel distortion; if the lines curve towards the center we have pincushion distortion.

authentic								forgery				
3	4	5	6	9	11	13	20	7	120	121	125	127

TABLE 1. References for the images used in our analysis and their category as authentic Bruegel drawings or forgeries.

When recording a photograph, the exposure heavily influences the visual appeal of the final photograph; if the exposure is too high the image is too bright in a non-homogeneous way and conversely the image is darker if the exposure is too low.

Both sharpening and increasing the contrast makes the edges in an image stand out more clearly. Since brushstrokes are very fine edges in a painting, the classification might benefit from enhancing those.

The rest of the paper is organized as follows: In Section 2 we present the data used in our experiments; in Section 3 we briefly recall our classification method from [6] and introduce the methods we use in this paper to test the robustness of our method. In Section 4 we present the results of our experiments and finally we draw conclusions in Section 5.

2. DATA

In [5, 7] the authors used images of drawings by Bruegel the Elder to test their classification methods. By courtesy of Daniel Rockmore of Dartmouth College, we have been able to test our methods on the same set of Bruegel drawings. With these images we obtain a good separation between the authentic Bruegel images and the known imitations, and hence we have chosen this data set for the current analysis.

The original Bruegel drawings stems from the Metropolitan Museum of Art in New York and in the following we refer to the drawings by their Metropolitan Museum of Art catalog number – as it is done in [7]. The image catalog numbers and their categories are summarized in Table 1.

The images consists of eight authenticated drawings by Bruegel and five acknowledged Bruegel imitations. In Figure 1 we have included an example of an authentic Bruegel drawing.

For our analysis all of the images were converted to grayscale using Matlab's rgb2gray command, which combines the three color channels of an RGB image into a grayscale version G by

$$G = 0.299R + 0.587G + 0.114B.$$

The majority of our work, including the image enhancements, has been carried out in Matlab version 7.11.0. However, changing the exposure of the images has been done using Apple Aperture, version 3.1.2. We will elaborate on this in Section 3.2.

3. METHODS

3.1. **Classification method.** Here we will briefly introduce our classification method from [6], which has been used for testing the impact of the different factors; the reader is referred to this paper for a more thorough survey.

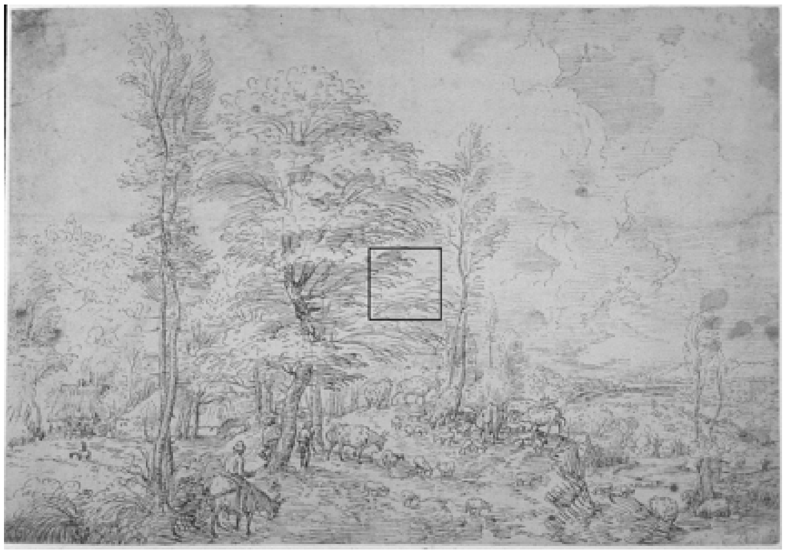

FIGURE 1. Example of an authentic drawing by Pieter Bruegel the Elder used in our experiments, namely the image 3 by the Metropolitan Museum of Art catalog number. The framed patch is the part we use for demonstrating the effects of the factors in later figures.

The basis for our classification method is working with the contourlet transform [3] of the digital images. In short, the contourlet transform is designed to provide a multiresolution representation of digital images with a *user specified* number of highpass orientations. The choice of the contourlet transform as the starting point of our classification gives greater directional information and we also avoid issues with applying continuous transforms on digital images.

The highpass subbands of the contourlet transforms contain among others the brushstrokes in a painting at a variety of orientations and resolutions. It is these subbands we model to obtain a classifier between authentic paintings and forgeries.

Statistical modelling of contourlet transform for classification/recognition purposes is obtained using hidden Markov trees; these have been used extensively for recognition purposes and was introduced for the contourlet transform in [8].

The idea is to model the highpass subbands in the contourlet transform that are related through the multiresolution analysis; this means that subbands at different resolutions are related if they have the same preferred orientations. When fitting a hidden Markov tree to a branch of subbands we investigate how the *structure* of the contourlet coefficients evolve as the resolution increases. This is an important distinction from object recognition in images – we are not interested in matching specific objects in the images, but rather the distribution of brushstrokes.

The hidden Markov trees used are parametric models. There are numerous parameters in the hidden Markov trees used and closed form solutions for the maximum likelihood estimates do not exist. Instead the parameter estimation is performed using an EM (Expectation Maximization) algorithm. The EM algorithm is an iterative procedure for performing maximum likelihood estimation, and as such, it needs an initial parameter estimate; this also means that the final parameter estimate depends on the initial estimate. To make our method less dependent on initial parameter estimates, we randomly generate a number of initial parameters, run the EM algorithm for each of them and choose the final model with the highest likelihood.

As a proxy of distance between paintings, we calculate a distance between the hidden Markov trees fitted to the paintings.

The distances between hidden Markov models is calculated as a weighted ℓ^1-norm of their parameters, where the weights are determined according to their impact on the classification of a suitable set of training images.

The basis of the classification is this proxy of pairwise distances between paintings.

After finishing the work in [6] we came up with a simpler way of utilizing the pairwise distances for classification.

The classifications in the present work have been performed using a k nearest neighbour method. That is, we classify a test image by a majority vote amongst the k training images with the smallest distance to the test image. A small difference from the usual k nearest neighbour algorithm is that we work *directly* with the distances between the hidden Markov models and not on an embedding of the distance via e.g. multidimensional scaling.

There are some things to keep in mind in this scenario.

- The small number of training images available puts restrictions on the number of neighbors available for classification, and when using only few neighbors, the variance is higher [4].
- The nearest neighbour of a point to be classified can be very far away – further than the distance between any training images. This is especially true if the image to be classified is a painting that looks completely different from the training material.

Besides the classification with a nearest neighbour procedure we can visualize the images and their interrelation by finding an embedding of points in $\mathbb{R}^2$ that respect their pairwise distances – this is obtained using a multidimensional scaling algorithm.

In the experiments we perform here, where we need to perform a large number of classifications, we need an automatic procedure. However, when confronted with the task of classifying a new images it would be unwise to rely solely on the automatic classification – among others due to the reasons listed above.

3.2. **Current experiments.** To estimate the impact of the factors we consider we have used the original data set described in Section 2 as a basis point for simulating images with the desired flaws.

We will now describe the procedures used to simulate the effect of the individual factors and the specific settings used.

1. Rotation of the camera is simulated by simply rotating the image. This introduces blank corners and a slightly smaller image after cropping. We have rotated the image at integer degrees between -4 and 4.

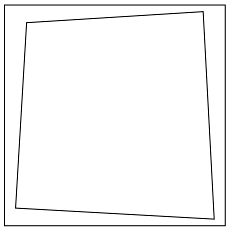

FIGURE 2. Example of keystone effect. Each of the corners in the large square is being mapped to the closest point in the smaller quadrilateral.

2. Keystone effect is a special kind of projective transform, identified by four control points. The idea is illustrated in Figure 2 – each of the corners in the large square is mapped to the closest point in the smaller quadrilateral, which is one of the control points. In our experiments the control points are determined by how much they should deviate from the side. For the keystone correction we have simulated ten uniformly distributed of control points. The points were then normalized such that the control points deviating the most was 2.5% of the side length.
3. Distortion is simulated by transforming the centralized polar coordinates of an image; the distance coordinate from the center of the transformed image s and the original image r are related by the equation
$$s = r + a \cdot r^2.$$
The sign of a determines the nature of the distortion – a negative a gives pincushion distortion and positive a gives barrel distortion. For the distortion we used the values $0, \pm 1 \cdot 10^{-5}, \pm 1 \cdot 10^{-4}$ for a.
4. Exposure is difficult to simulate and here we have employed a black box in the form of Apple Aperture. In Aperture we adjust the exposure relative to the current value, where a lower exposure darkens the image and a higher exposure brightens the image. We have adjusted the exposure with $\pm 0.5, \pm 0.25, 0.75$ and left it untouched at 0. The visual appearance of the different exposure values is illustrated in Figure 3.
5. Sharpening in Matlab is performed with a modified Laplacian filter, whose shape is controlled by a parameter varying in the unit interval. For the parameter we used the values 0 and 0.2.
6. Initially we increased the contrast of an image by saturating a percentage of the brightest and darkest pixels. This way of increasing the contrast is a non-invertible transform.

For the saturation we discarded 0, 2, 4, and 6 % of the brightest and darkest pixels.

As explained in Section 4 we later decided to use another approach to increase the contrast that preserves information. This involves specifying the shape of the curve describing the relation between the bright and dark colours in the input and output image. The shape is controlled by a parameter γ, which is the power of the intensity values – as illustrated in Figure 4. The visual effect of the different contrast increasements is demonstrated in Figure 9.

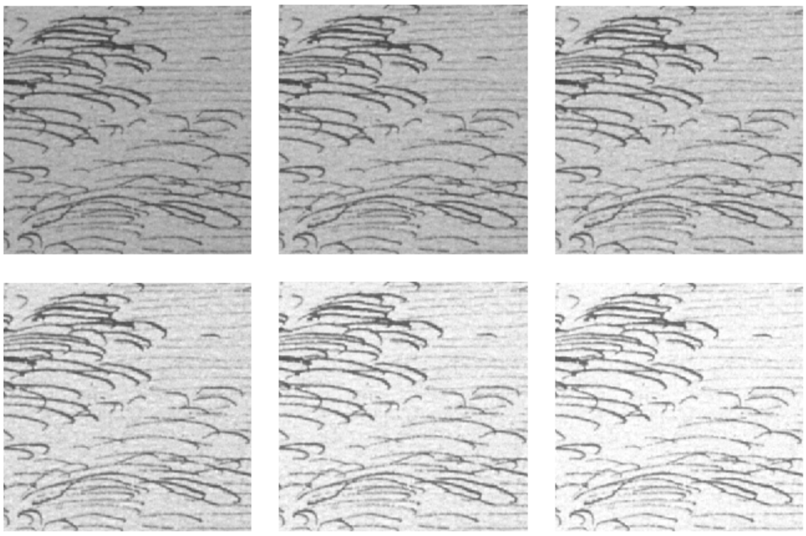

FIGURE 3. Examples from the image 3 with the exposure adjusted. From the left to right the exposure correction is −0.5, −0.25, 0 (original image) in the top row and 0.25, 0.5, 0.75 in the bottom row.

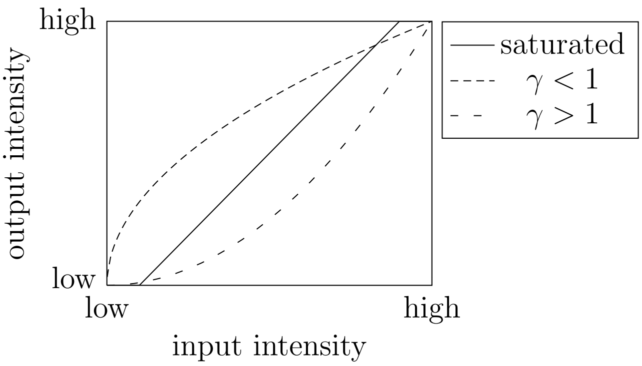

FIGURE 4. Shape of different contrast curves.

As mentioned above we think that it is natural to group the factors into two groups – namely those related to the positioning of the camera, 1 and 2, and those related to the recording properties of the camera, 3 – 6.

To test the influence of the factors we perform a factorial experiment for each of the two groups. For the positioning experiment we have a total of $9 \cdot 10 = 90$ combinations and for the camera experiment there is a total of $5 \cdot 6 \cdot 2 \cdot 4 = 240$ combinations.

The final goal of a classification method is to have a high rate of correct classifications; hence when making conclusions about the impact of a particular factor, the most important question is whether or not the correct classification rate is significantly downgraded.

We estimate this in two ways, namely by performing leave-one-out cross-validation and by classifying the simulated error images with the original images.

The reason for including the classification method is that all the effects we apply to our images are *relative* to the original data set, so if a factor has a negligible effect we should be able to classify them correctly with the original images.

As mentioned in Section 3.1 our model is fitted using an iterative procedure that relies on an initial parameter estimate, resulting in a final model that also depends on the initial estimate. Therefore, we can not expect different runs to yield exactly the same final model. In order to draw conclusions about the effects of the factors we are interested in, we therefore need to gain insight into the effects of the EM algorithm.

This is done by training a number of models on the original images and see how these models behave compared with one of these model, which we have chosen as a reference.

In relation to this experiment there are some interesting questions:

(1) Is the variation caused by the EM algorithm homogeneous amongst the paintings?
(2) Is the variation caused by the EM algorithm so large that it effects the classification?
(3) Is the variation by the factors 1 – 6 greater than what can be expected from the EM algorithm?

4. Results

The images we have used as training data for the classification scheme are well separated: When performing leave-one-out cross-validation 11 of the 13 images are classified correctly using both 1 and 3 nearest neighbour classification. Neither case can classify the image 125 correctly; as illustrated by Figure 5 this is due to the fact that the image 125 is far from *both* the authentic training images as well as the other known forgeries.

The first thing we have done is to test the influence of the EM algorithm: We have trained 30 models from the original images and tested the classification scheme on these. For each of the models we compute the pairwise distances to the reference model. An embedding of points illustrating the pairwise distances is presented in Figure 6.

We want to test whether the distances from the trained model to the reference model are the same for each image. The distributions of these distances are not of the same shape and it is therefore not appropriate to test this hypothesis with an ANOVA or a non-parametric equivalent relying on assumptions about the shape of the distributions.

Instead we apply a permutation test to test the hypothesis that the distribution of distances within each image are the same. This hypothesis is rejected without doubt, as one would expect from the box plots of distances in Figure 7.

Even though the EM algorithm does introduce variation, it is not so severe that it influences the classification; using a 1 nearest neighbour classification all of the test models are classified correct – as is expected if the variations are reasonably small. As can be seen from Figure 6 using more than the nearest neighbour is not likely to correctly classify the image 125 – a point might have this as it nearest neighbour, but the second and third nearest point is likely to be an authentic image. On the other hand we might experience the opposite problem amongst the images that are closer (both authentic and forgeries); the closest

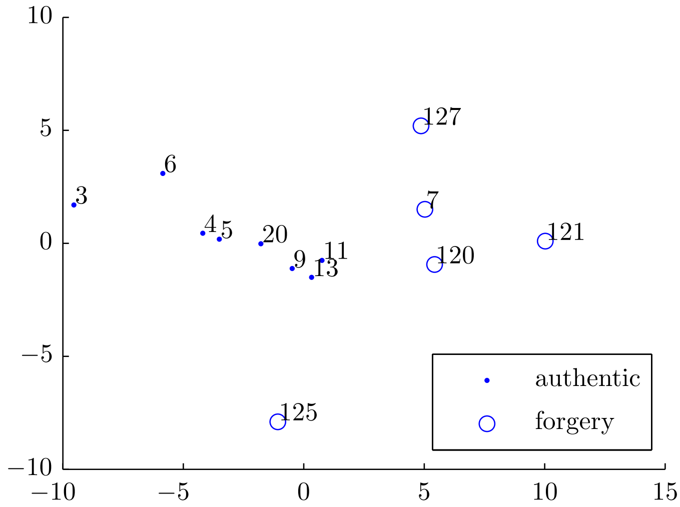

FIGURE 5. Visualization of the relationship between the training images; an embedding of points in $\mathbb{R}^2$ whose pairwise distances resemble those computed for the images.

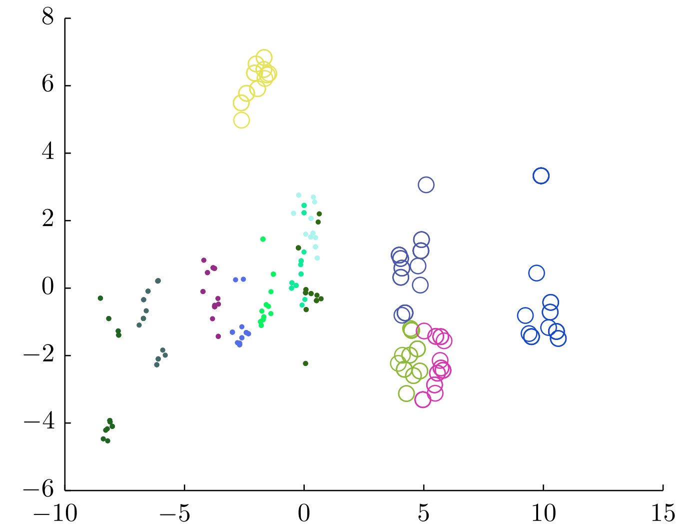

FIGURE 6. Visualization of the variation in the models introduced by the EM algorithm. The models are coloured according to the image they represent; authentic and forgeries are represented using the same symbols as in Figure 5.

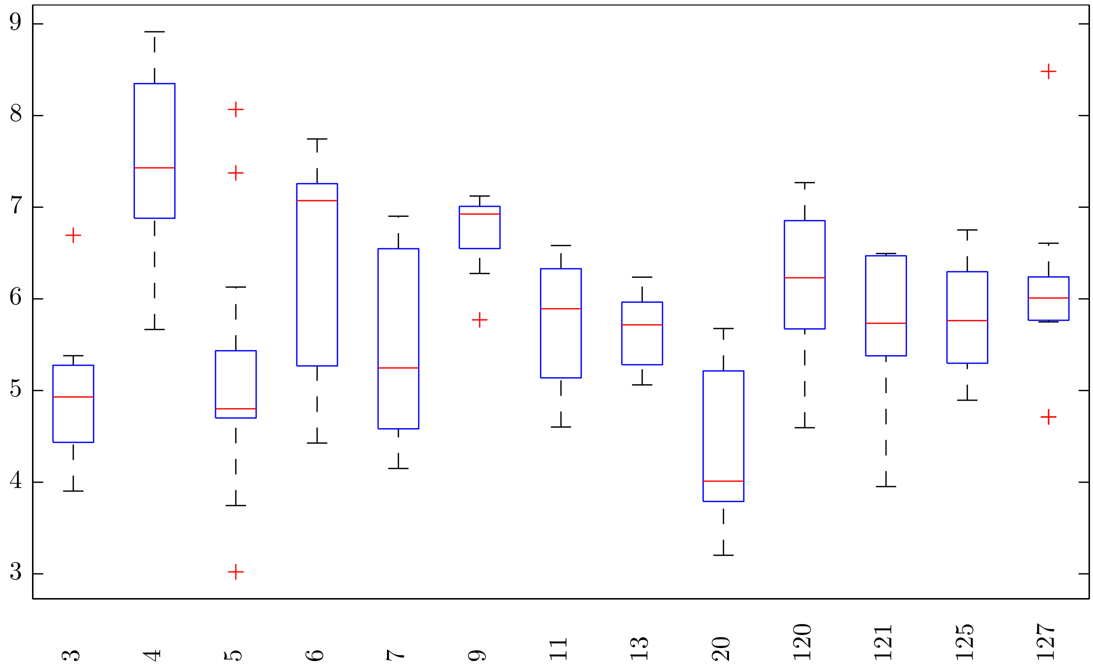

FIGURE 7. Box plots of the distances from each of the models trained on the original images to their reference model.

k	rotation in degrees								
	-4	-3	-2	-1	0	1	2	3	4
1	0.97	0.97	0.99	0.98	0.98	0.98	0.97	0.97	0.98
3	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92

TABLE 2. Proportion of average correct classifications for the positions experiments with k nearest neighbour classification.

neighbour might be of the wrong class, but the second and third closest neighbour is of the correct class.

4.1. **Position experiments.** Regarding the positioning experiments with the factors 1 and 2, we have computed the classification error for each of the combinations and tested the variation of distances. The latter is performed individually for each image (due to the non-homogeneity of distances between the models of the reference images); we test if the distances for a fixed value of 1 are of the same order of magnitude as the reference models.

For the majority of the position experiments, the variation of distances are significantly higher than for the reference models. However, these factors have only little influence on the classification probabilities that are almost perfect with both 1 and 3 nearest neighbour classification – as seen in Table 2.

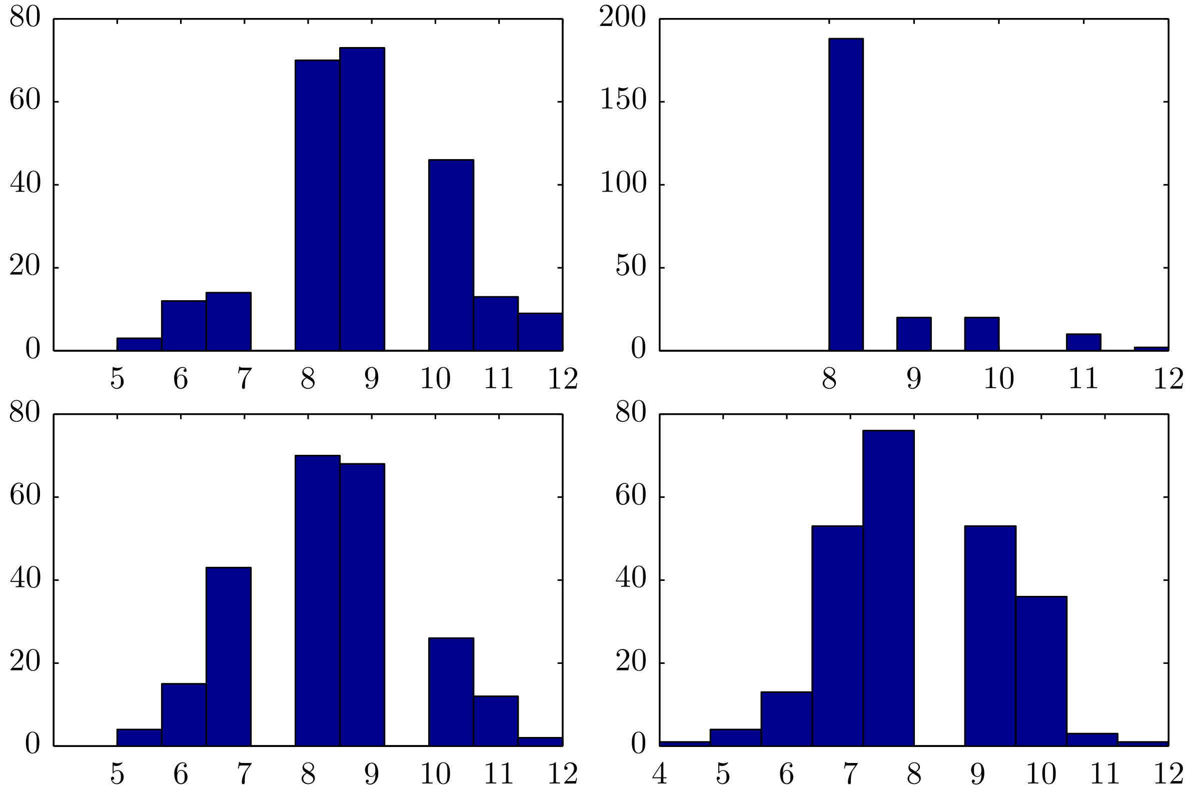

FIGURE 8. Histograms over the number of correctly classified images in the camera experiment. The top row is for classification with the reference model and the bottom row is for cross-validation. The left column is from classification using 1 nearest neighbour, while the right column is using 3 nearest neighbours.

Performing the same experiments for the camera experiment, related to factors 3 – 6 we do not obtain as good classification results, but the results are interesting.

The number of correctly classified images varies between 5 and 12 out of the 13 possible with 1 nearest neighbour and between 8 and 12 for 3 nearest neighbour. As can be seen in Figure 8 the majority of the factor combinations have low classification rates.

Out of the 240 different combinations of factors roughly a quarter gets more than 8 correctly classified images with 3 nearest neighbours – and the common feature for all of these is that the contrast has not been increased.

After observing this effect from increasing the contrast, we examined the images with higher contrast and noticed that it disrupts the finest details – the very details we are interested in modelling. We have included examples of this in Figure 9.

The reason the brushstrokes gets corrupted by the contrast increasement is because the saturation (as explained in Section 3.2) introduces artifacts like enhancing the background so that it could look like brushstrokes.

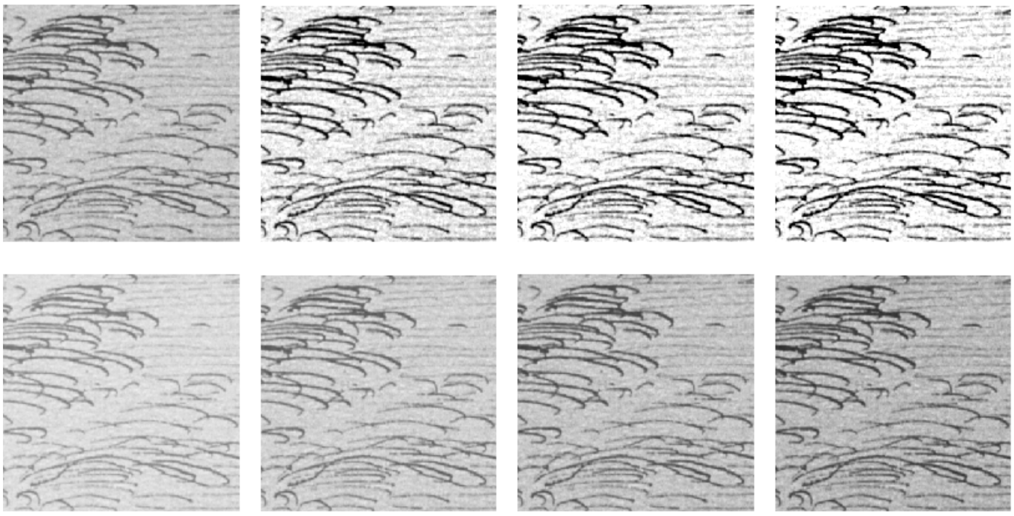

Figure 9. Examples of the effect of increasing contrast in a patch from the image 3. In the top row we have from left to right saturated 0, 2, 4 and 6 % of the pixels. In the bottom row we have the same patch with different values of γ; specifically, the values from left to right are 0.5, 0.7, 0.9 and 1.1.

		contrast curve γ											
k	kind	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	1.1	1.2
1	class	5	5	6	5	8	12	11	13	13	13	13	13
1	cross	9	11	11	12	10	11	12	12	12	12	10	7
3	class	5	5	6	5	10	13	12	13	13	12	12	12
3	cross	9	10	10	10	11	11	11	12	12	11	10	9

Table 3. Number of correctly classified images for the different contrast images parametrized by γ. The number k is the number of nearest neighbours used in classification. “kind” refers to the classification: “class” is classification by the reference models and “cross” is leave-one-out cross validation.

There are many ways of increasing the contrast in an image; any non-decreasing, bijective function on the intensity values qualifies for this task. Since our first approach to increasing contrast had such a substantial negative effect on the classification, we found it interesting to see if other contrast functions could improve the classification.

We therefore applied another contrast increasement function as explained in Section 3.2. The effect of this contrast increasement can also be seen in Figure 9.

The results from using this approach to increasing the contrast is presented in Table 3.

A notable thing is that for images with contrast curves that has γ slightly less than 1, the cross-validation success rate is higher. The image that is not classified correctly in the cross-validation with 3 nearest neighbours is the image 125, that is very different from the rest of the images.

The reason the number of correct classifications decrease so significantly for low values of γ is that the models look different from *all* the training models.

5. Conclusions

When applying a classification method to determine the authenticity of a painting, the method should not be too sensitive to small variations in the digital reproductions of the paintings. In this paper we have modelled a number of factors that one is likely to encounter when acquiring digital reproductions and tested their influence on our classification method from [6], that is based on second generation multiresolution analysis.

The factors related to the position of the camera relative to the paintings do not have a significant effect on our algorithm. The factors related to the recording properties of the camera can have some effect – especially the contrast of the image is influential if increased the wrong way.

The experiments yielding negative effects of increasing the contrast by saturating extreme intensities led us to investigate if other contrast enhancements could have a positive effect on the classification. Indeed, by increasing the contrast in a loss-less manner, our classification methods perform better.

Based on the experiments presented in this paper, we believe that our algorithms are suitable for real world data.

6. Acknowledgements

We are very grateful to Daniel Rockmore for providing us with the Bruegel images used in our experiments.

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