

TECHNICAL PAPER

WATERCOLOUR IDENTIFICATION BASED ON MACHINE VISION ANALYSIS

Vassiliki Kokla, Alexandra Psarrou*, Vassilis Konstantinou

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Guest editor:
Prof. Dr. Manfred Schreiner

University of Westminster, Harrow
School of Computer Science, Watford
Road, Harrow, Middlesex, HA1 3TP,
U.K.

corresponding author:
psarroa@wmin.ac.uk

In this paper we present a novel image-based approach for characterizing and classifying blue and green pigments as used in paintings based on their optical properties. Our aim is to develop a non-destructive method that can characterize and classify watercolours through a statistical approach which recognizes both the probabilistic nature of the optical watercolour information and the form in which we should express the results. Furthermore, this study also combines historical information and the statistical computation of the watercolour optical behaviour.

Our method is non-invasive, does not involve sampling and can be applied in situ. It is based on the optical properties of pigments as well as the correlation of pigment variations. Such variations are studied using co-occurrence matrices that capture the behaviour of the pigments during the painting process. Furthermore, the optical response of watercolour pigments can be represented using a mixture of Gaussian functions, and can be classified using a Bayesian decision rule.

1 Introduction

The aim of this study is to develop a non-destructive method that can characterize and classify watercolours through a statistical approach which recognizes both the probabilistic nature of the optical watercolour information and the form in which we should express the results. Furthermore, this study combines information on historical literature for the watercolour pigments.

The watercolour pigments can be a combination of inorganic or organic pigments or both. As the watercolours are the main element in the production of illustrations, therefore their analysis is important for the art historians, artists, art dealers and the scientists who study the works of arts on paper. Most of existing methods used for the examination of pigments are based on destructive testing techniques that require the physicochemical sampling of the painting under test. Such

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methods are not allowed by curators to be used in watercolour analysis because of the required amount of sample used in these methods.

Image-based techniques have been recently used in order to examine and interpret the optical characteristics of pigments in various areas of the electromagnetic spectrum. For example, visible reflectance spectrophotometry was used to evaluate potential pigment combination in painting,¹ multi-spectral image analysis and its application in art image classification.² Some of the image-based methods used on materials found in works of art are focus on composition, rather than analysis, and are mainly applied in the restoration of colours in paintings.³

This study is based on the optical properties of the pigments in visible area as well as the correlations of pigment variations. Such variations are studied using co-occurrence matrices that capture the behaviour of the pigments during the painting process. Furthermore, the optical response of watercolour pigments can be represented using mixture of Gaussian functions, and their optical features can be classified using Bayes' decision rule and image variations.

In the remaining sections of this paper we first give a short description of the composition of pigments that were used for this study. In Section 2 we present the methodology that we have followed. Results for the classification of watercolour pigments are given in Section 3, and finally in Section 4 we present our conclusions.

1.1 Background

Pigments used in watercolour paintings are usually a mixture of microscopic pigment particles in a binder that permits particles to be applied with a brush and subsequently dry to bind the pigment to the support.⁴ The most often binder used in water-

Chemical pigments categories				
Pigments used	Inorganic	Organic	Natural	Synthetic
Blue Black		X	X	
Cobalt Blue	X			X
Cobalt Green	X			X
Cobalt Turquoise	X			X
Indigo		X	X	
Chromium Oxide	X			X
Prussian Blue	X		X	
Terre Verte	X		X	
Ultramarine	X			X
Viridian	X			X

Table 1. The chemical composition of watercolour used.

colours is gum arabic made from Acacia trees. The watercolours which we used in this study consist of blue and green shaded pigments (Table1).

We chose these pigments for the following reasons:

- they have a wider range of chemical composition than other pigments
- they have a wider range of radiation absorption than other pigments
- they are most commonly used of the watercolour artworks.

Direct observation and examination of inks under normal light can provide some preliminary clues towards their identification but this alone is not sufficient to discriminate between the different pigments. Obviously, pigments of similar colour have very similar intensity values. Thus, the intensity distributions of pigments can be represented through a mixture of Gaussian functions (Figure 1) and their optical features can be classified using a Bayesian decision rule which allows us to weight the probability of intensity values of pigments.

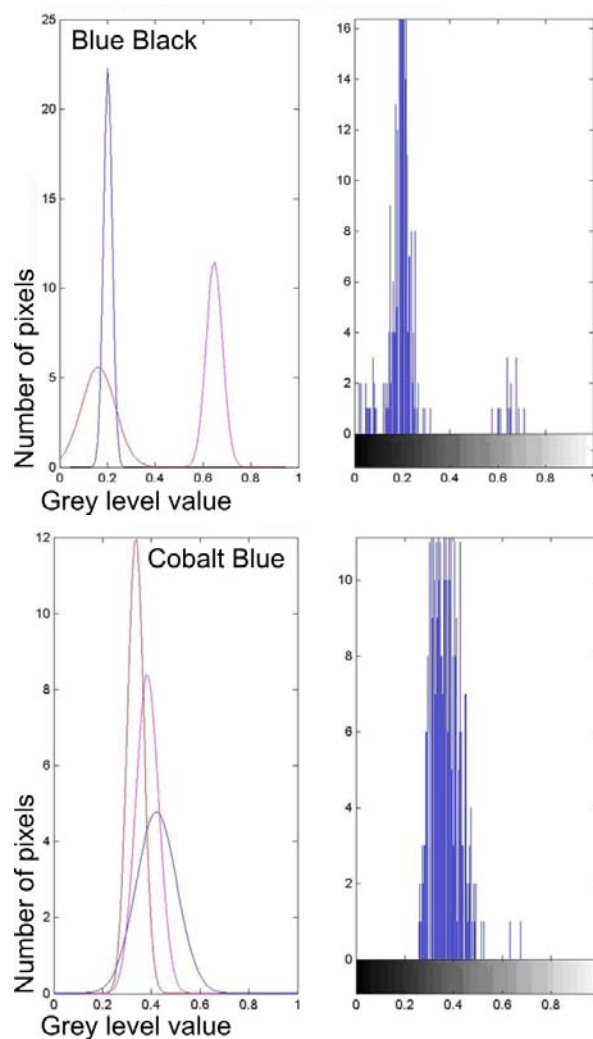


Figure 1: Examples of Gaussian mixture models of pigments under visible radiation.

To aid the classification of these pigments we also consider some additional physical characteristics such as the behaviour of the pigments during the painting process. This characteristic is examined by studying the image variations using co-occurrence matrices.

2 Methodology

2.1 Pigment Images and Image Segmentation

The images used during our experiments can be separated to those of known chemical composition and include model images and those of unknown chemical composition that were taken directly from authentic watercolour paintings. In model images include watercolour pigments with known composition. These pigments have been fabricated to reflect the painting conditions that are found in watercolours. In Figure 2 we can see examples of watercolour pigment images produced using 1 to 4 layers of pigment to simulate varying pigment thickness during painting. Figure 3 shows images that were taken from authentic watercolour paintings and their pigments are of unknown chemical composition.

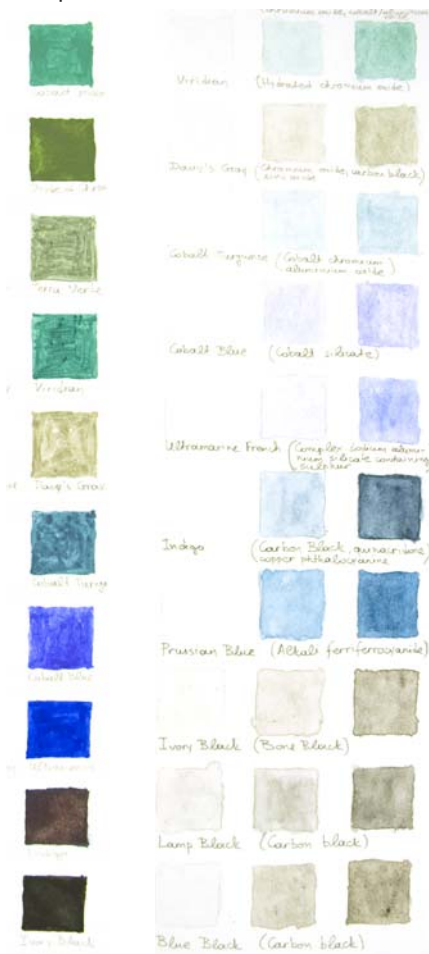


Figure 2: Watercolour pigments.

Using the HSV domain we could choose the colour area of interest that we were going to analyse. As pigments used in watercolours are transparent and their reflective properties are affected by the thick-



Figure 3: Authentic watercolour paintings.

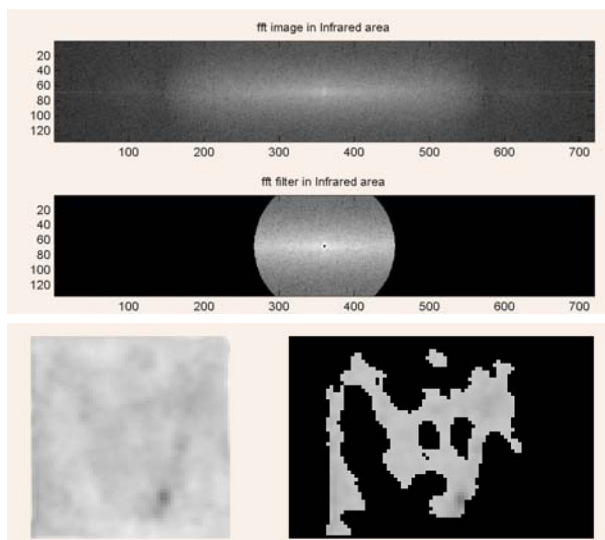


Figure 4: Top two rows: Example of fast Fourier transformation and band-pass filter. Two columns last row: Example of the result of standard pigment images after the use of band-pass filters.



Figure 5: a) original image; b) saturation image from HSV domain; c) selected colour area based on HSV domain; d) selected area using band-pass filter in fast Fourier domain.

ness of the liquid used (pigment and binder) and the reflective properties of the underlying support,⁴ we apply Fourier transforms to locate the “thickest” points and separate them from the rest of the image.

This is achieved by means of band-pass filters (Figure 4) which select frequencies within certain ranges, thus enabling the isolation of areas with the largest amount of pigment. The EM algorithm⁵ is used to segment these areas from the background. In other words we create an electronic “mask” to isolate the areas which contain the maximum amount of pigment (Figure 4). Figure 5 shows an example of the segmentation steps in authentic watercolour paintings.

2.2 Analysis of Pigment Images

2.2.1 Characterization of Image Variations

In the isolated pigment areas of the images we apply co-occurrence matrices in order to compute the images variations that characterize each pigment.⁶ Although pigments may have similar chemical composition, they exhibit different painting behaviour due to their difference in fluency and their spread on the support. Such variations can be captured in co-occurrence matrices that are used as the underlying structure for storing the distribution of the pigments during the painting process. The co-occurrence matrix describes the relationships of neighbouring pixels in the pigments, based on the distance d between two pixels in any direction. The direction between the two pixels is a concern, and this is implemented by multiple matrices, for four directions: horizontal, vertical and two diagonals. Employing the method of the grey level co-occurrence matrix, models are created for each layer of each pigment. For all model pigments co-occurrence matrices are formed in angles of 0° , 45° , 90° , 135° degrees and distance ($d = 1$) of neighbouring pixels.

Typically the co-occurrence matrices used record intensity values between 90-200, therefore the size of a co-occurrence matrix is approximately 110×110 . The measurements in the co-occurrence matrices are normalized and therefore the results are independent of the size of the images. Computing the correlation of neighbouring pixels with the co-occurrence matrix produces sets of characteristic variations for each model pigment.

Co-occurrence matrices obtained from the pigment images are compared by calculating the Euclidean distance between the co-occurrence matrices x and y given by:

Blue Black pigment in four layers in four co-occurrences

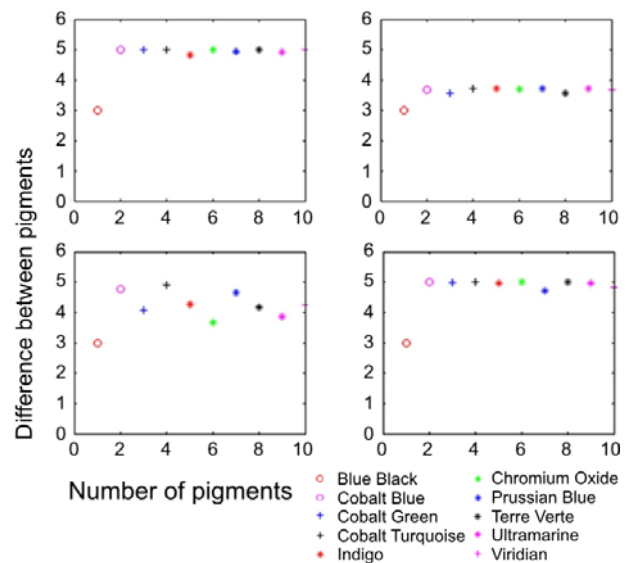


Figure 6: Example of comparison of co-occurrence matrices.

$$h(x,y) = 1 / \|x-y\| = 1 / ((x_1-y_1)^2 + \dots + (x_n-y_n)^2)^{1/2}$$

An example of the comparison between the model pigments and one of the images that contributed to the computation of the models is shown in Figure 6. Each coloured graph represents the difference between the model pigment and the pigment in the image in question. On x-axis are listed the ten pigments and on y-axis we record the difference $h(x,y)$ of the pigment in question from the model pigment. The lowest point in the graphs indicates the model pigment recognized as the pigment used in the image in question. In this example we can see that in all cases this pigment has been recognised as the correct pigment.

2.2.2 Pigments Classification using Bayes' Theorem

We examine pigment images in the areas containing the “thickest” layers of pigment to decrease the problems associated with “noise” introduced by the reflection of the support. For this reason, we used Gaussian mixture models for modelling intensity values of the pigment in these areas. In Figure 1 we can see that when histograms are similar then the Gaussian mixture model can help in the discrimination of different types of pigments. Figure 1 shows two examples of Gaussian mixture model representations. This occurs, because a pigment distribution can be represented as a weighted sum of basic pigment model components through Gaussian mixture models. These model components are different, although, they describe often similar distributions of pigments. EM is a widely used method for estimating the parameter

Viridian in four layers

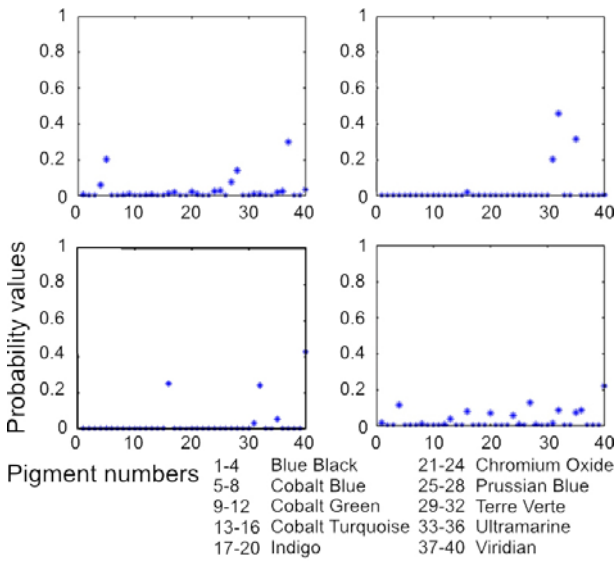


Figure 7: Examples of Viridian analysis using probability classification.

set of the pigment model. The classification of pigments was done using Bayes' theory⁵ which can analyze pigment distributions with respect to each intensity value of distributions.

In the cases with the unsatisfactory classification results, a closer examination of the Gaussian mixture models reveals that in most pigments there were large weighted components with grey levels of the same intensity values. In order to discriminate differences among the various pigments with similar intensities, we took into account the likelihood of each intensity value to occur in a pigment compared to the overall occurrence of this value in the pigment images.

An example is presented in Figure 7 which shows the likelihood results for viridian watercolour pigment. The x-axis depicts the ten pigments in the four different thickness layers (1-40). The y-axis indicates the probability values. This graph shows that this pigment was identified as viridian in three layers and as ultramarine in one layer.

2.3 Comparison of Pigments

In order to validate our image-based classification, we compared the pigment models with each of the images that contribute to the creation of the models. The results indicate that in most cases the identification of pigments is feasible. The results fall into three categories:

- Successful. A result is to be considered as successful when the correct model pigment is identified.
- Screening. A result is to be considered as screening when the correct model pigment is

included among the first three results.

- Unsuccessful. A result is to be considered as unsuccessful when the correct model pigment is not included among the first three results.

We used the same comparison and the same categories of results between pigment models and pigments from authentic watercolour paintings.

3 Results

3.1 Image Variations Using Co-occurrence Matrices

The results are based on the computation of the four co-occurrence matrices under visible illumination. Examination of the results shows that all pigments can be identified with 100% success rate.

Blueblack pigment in four layers

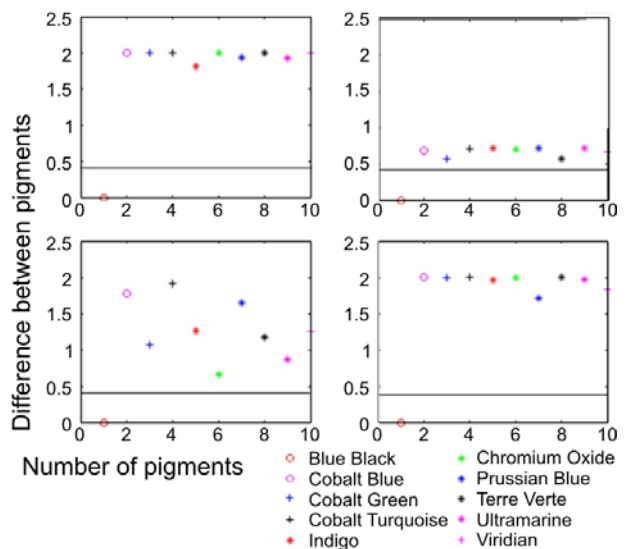


Figure 8: Example of the strength of results based on threshold value.

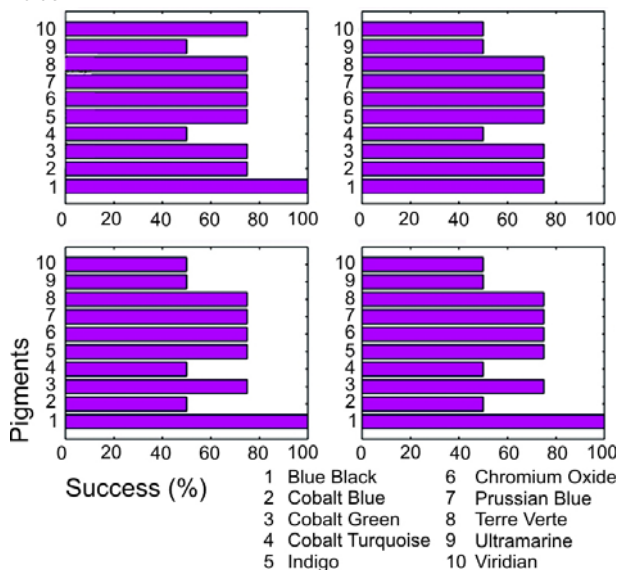


Figure 9: Strong results of pigments for four co-occurrence matrices.

Paintings	Pigments									
	Blue Black	Cobalt Blue	Cobalt Green	Cobalt Turquoise	Indigo	Chromium Oxide	Prussian Blue	Terre Verte	Ultramarine	Viridian
Painting 1					X V					
Painting 2						X V				
Painting 3 Blue					X V					
Painting 3 Green1						X V				
Painting 3 Green2	V									X
Painting 4 Blue		X			V					
Painting 4 Green1	X V									
Painting 4 Green2				X				V		

Table 2: Results of pigments from authentic watercolour painting (V indicates the results from image variations and X the results of probability classification). Probability results of pigments.

Because of the great percentage of success, we computed the strength of the results in order to determine the accuracy of the method. Figure 8 shows the percentage of successful identified models below the threshold value of 0.3 (strong results) and the percentage of the correct identified models above the threshold value (weak results).

We used the same threshold value in four co-occurrence matrices. Looking at the results in Figure 9 we can make the following observations:

- The majority of the successful results were strong therefore giving us strong belief in the outcome of the results.
- Although in most cases the results are strong, in thin layers the results are weak. The only exception is the Blue Black pigment, which presents strong results in most cases.

3.2 Pigments Classification Using Bayes' Theorem

Figure 10 shows the percentage of the successful and screening results when the pigment models are tested against images that were incorporated in the computation of the model pigments. The results are based on the computation of the intensity probabilities of pigments. The following is observed:

- Eight out of ten pigments were successful and screened.
- Cobalt Turquoise, Ultramarine and Viridian pigments were successful with a rate of 100%.
- Chromium Oxide and Prussian blue pigments were successful and screened. The corresponding successful and screening results for both pigments are 100%.
- Indigo and Terre Verte pigments were successful and screened with lower percentage of success,

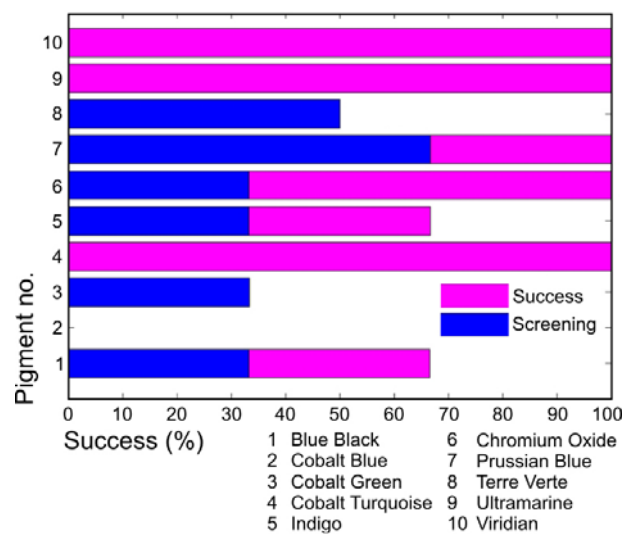


Figure 10: Probability results of pigments.

their results being 67% and 50% respectively.

- Cobalt Blue and Cobalt Green pigments cannot be identified.

3.3 Classification of Pigments from Authentic Paintings

Taking account the colour of pigment from authentic paintings we compared images of model pigments with pigment images from authentic paintings. Table 2 shows the pigment results from image variations and Bayes' classification. The symbol V indicates the results from image variations and the symbol X indicates the results of probability classification. We observe that five out of eight results are similar. We note that:

- Case of Painting3 Green2. Blueblack pigment is found among of three first results in both classifications.
- Case of Painting4 Green2. Cobalt Turquoise is found among of three first results in both classifications.

4 Conclusions

In this paper we propose an image-based method for the discrimination of watercolour pigments that is based on the pixel variations and the probability classification of pigment pixels through of Gaussian models of diverse types of pigments. This method can be applied in any watercolour painting in the place where it is. Based on the results presented we can conclude that statistical analysis and discrimination of pigments using image variations and Bayes' classification can provide reliable information towards the identification of watercolour pigments.

Although the identification of model pigments in our tests was confirmed to be either successful (correct identification) or within the screened category (correct pigment amongst the three most likely pigments), further work is underway to validate the results of pigments from authentic paintings. Furthermore the pigment results of authentic paintings should be verified through other non-destructive methods. However, we note that in previous works⁷ on manuscript inks – the chemical composition of inks is similar with the chemical composition of watercolour pigments - we managed to recognise an adequate number of inks from authentic manuscripts.

5 Acknowledgements

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6 References

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