Ink recognition based on statistical classification methods.

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Abstract

Statistical classification methods can be applied to images of historical manuscripts in order to characterize the various kinds of inks used. As these methods do not require destructive sampling they can be applied to the study of old and fragile manuscripts. Analysis of manuscript inks based on statistical analysis can be applied in situ*, to provide important information for the authenticity, dating and origin of manuscripts.*

This paper describes a methodology and related algorithms used to interpret the photometric properties of inks and produce computational models which classify diverse types of inks found in Byzantine-era manuscripts. Various optical properties of these inks are extracted by the analysis of digital images taken in the visible and infrared regions of the electromagnetic spectrum. The inks are modelled based on their grey-level and colour information using a mixture of Gaussian functions and classified using Bayes' decision rule.

1 Introduction

The aim of this work is to use image-based techniques to complement the reflectographical methods of analysis. This is done by developing computational models for the interpretation of the photometric properties of the inks in the visible and infrared regions of the spectrum, thus providing an *in situ* and portable quantitative method for the identification of inks used in old manuscripts. To develop a generic framework which formulates solutions for ink recognition problems, we need a statistical approach which recognizes both the probabilistic nature of the optical ink information we seek to process, and and the form in which we should express the results.

The replica manuscript inks we examined, were made using a combination of inorganic and organic pigments such as metals, salts and vegetable materials. Existing methods used for the examination of pigments can be applied in the analysis of manuscript inks, however, most are based on destructive testing techniques that require the physicochemical sampling of the manuscript under test. Such methods cannot be used widely for manuscripts mainly because of their historical value. Non-destructive techniques such as reflection spectroscopy and reflectography where the optical properties of the pigments are examined under illumination beyond the visible spectrum, are well suited to the study and conservation of old manuscripts.

Related machine vision research in the analysis and modeling of color [7], focuses mainly in the visual retrieval of information in the form of digital image libraries [21, 12, 17]. Most of the image-based research on materials used in works of art are focused on generation, rather than analysis, and are mainly applied in the restoration of colors in paintings and frescoes [18, 19, 24]. Granado used mathematical morphology to identify and extract several stylistic components used in antique printed books such as drop capitals, stripes, figures, annotations and text matters, in order to build metadata automatically [13].

In recent years, attempts have been made for the analysis of pigments using electronic video imaging devices in reflectographic and radiographic techniques. These attempts are few and fragmented. Some of the most relevant are:

- The examination of underdrawing lines in artworks [4].
- The use of vidicon TV cameras for infrared reflectography on artworks [16].
- Platinum silicide cameras for use in infrared reflectography on artworks[22, 23].
- A more sophisticated approach using band-pass filter reflectography, which helps to discriminate between types of inks [11, 10].
- Radiographic techniques and new imaging technologies used in the study and conservation of paintings [20].

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- The analysis of Anglo-Saxon manuscript pigments with non-destructive techniques[3].

- A method for the elimination of cracks in infrared reflectograms that show the underdrawing - the basic concept of the artist drawn on the ground layer - in ancient wood panel paintings [14].

Manuscript inks, however, are semi-transparent pigments and difficult to characterize because their intensity depends on the amount of liquid spread and absorbed during scripting and the reflective/scattering properties of the substrate or support.

In this research we show that the photometric response of manuscript inks can be represented in the visible and infrared regions of the spectrum through a mixture of Gaussian functions, and their optical features can be classified using Bayes' decision rule.

In the remaining sections of this paper we first give a short description of the composition of inks that were used for this study and present the model and test images used. In Section 3 we present the analysis of the inks. Sample results for the classification of manuscript inks is given in Section 4, and finally in Section 5 we present our conclusions.

2 Background

The majority of manuscript texts have usually been written in black, brown or brown-black inks as evidenced by the the cataloging of such manuscripts in museums and libraries. This descriptive term, however, does little to indicate the richness or variety of tones of the inks which fall within this category. The two most common - brown, black or brown-black - writing fluids were composed of either carbon or metalgall[2]. The carbon inks were composed generally of either soot, lampblack, or some type of charcoal to which gum arabic and a solvent such as water, wine, or vinegar was added. The basic ingredients of metalgall inks are copper, iron, galls, gum arabic, and a solvent such as water, wine, or vinegar[5], [9].

The inks used in this study date from the 11th to the 18th century and are employed in manuscripts located in south-east Europe and the eastern Mediterranean, especially in areas where the Byzantine Empire and its influence had spread. Furthemore, the language used is Greek.

The first aim of our study was to derive mathematical models for the inks manufactured according to the recipes given in[25] in order to have a basis for comparison with unknown manuscript inks. We prepared eight inks with various known chemical compositions, in order to represent as many types of ink as possible. These are as follows:

- Carbon ink

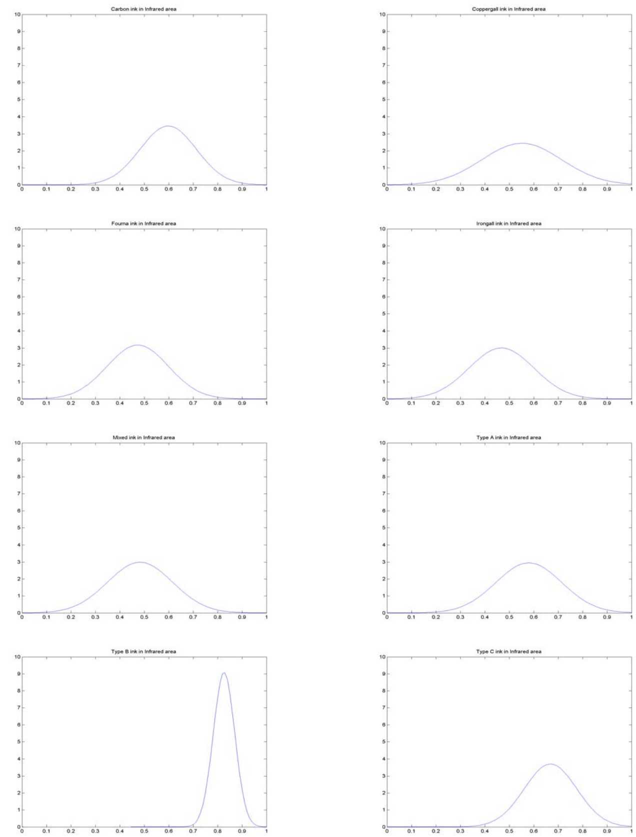

Figure 1. Intensity distribution of inks under infrared radiation.

- Metalgall ink. (This category contains the Coppergall inks and Irongall inks.)

- Incomplete ink. (This group includes ink, that have a similar composition to that of metalgall inks, although their composition does not include all of the ingredients of metalgall inks and we treat them as subclasses of metalgall inks(type A,B and C)).

- Mixed ink. (This category contains inks that have ingredients of the first two categories).

Reflectographical studies of the optical behavior of the inks under visible and infrared radiation have shown that those inks which appear to have very similar photometric properties under visible light, and cannot be differentiated, can be identified when viewed under infrared light[1]. This is due mainly to the different chemical composition of the inks. The brightness values of each type of ink under infrared radiation can be modelled through characteristic intensity distribution curves. The modelled intensity distribution of eight types of inks are given in Figure 1 and show

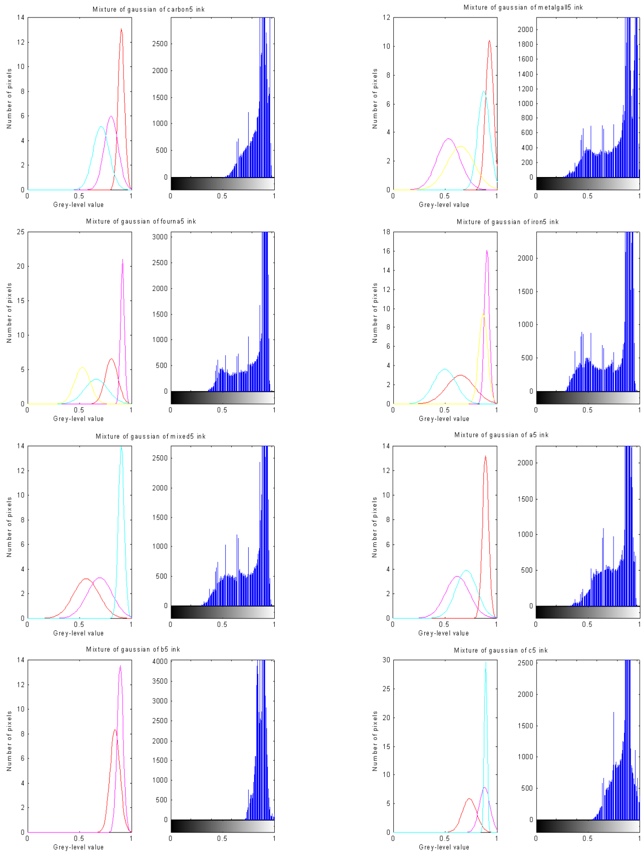

Figure 2. Examples of Gaussian mixture models of inks in the infrared.

clearly, that even though there is a difference in the intensity distribution of inks under infrared radiation, this alone is not sufficient to discriminate between the different inks. One of the main reasons for the uniformity of the results obtained is that when inks are transparent their reflective properties are influenced by the thickness of the ink used and the reflective properties of the underlying support[6]. However, we show here that using a mixture of Gaussian functions results in a more accurate representation of the different types of ink present in the manuscripts. This allows the decomposition of the intensities found in an ink, and therefore the diversity in the ink models, as shown in Figure 2. Having modelled the inks, Bayes' decision rule can then be used for their classification.

In addition to intensity, the model inks are studied for their colour information, described as Hue (H) and saturation (S). Figure 8 shows the mean and standard deviation measurements for the hue and saturation values of the inks. It can be seen that in general that the inks cannot be differentiated based on their hue value. Type A inks are an exception.

By studying the HS values of brown, brown-black and black inks we observe that even though there is not enough information to discriminate the inks based on hue alone, there are differences in the saturation values which will distinguish them.

2.1 Ink Images

Our experiments were also concerned with creating images to reflect the scripting conditions found in manuscripts which encapsulate:

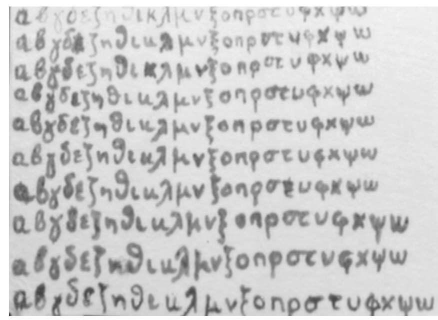

Figure 3. Example of grey-level model images.

- The varied thickness of the inks during scripting.
- The varied scripting formed due to the different means of writing used, such as quill, calamus and penna.
- The writing characteristics of different scribes.

The images used during our experiments can be separated as those of known chemical composition, which include both model and test images, and those of unknown chemical composition that were taken directly from Byzantine and Post-Byzantine manuscripts, where an X-Ray Fluorescence Spectrographic (XRF) method [15]is employed to validate the ink composition used in the manuscript. Figure 3 shows examples of grey-level model images produced using 1 to 10 layers of varying thickness inks during scripting. A total of 480 images (8 inks x 10 layers x 3 pens x 2 cases letters) of the Greek alphabet were created in both grey-level and color areas. These were grey level images and included all categories of inks, writings produced by various script materials and different script styles.

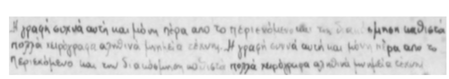

Figure 4. Example of test images.

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The test images included scripts produced with inks of known composition and scripts taken from Byzantine and Post-Byzantine manuscripts. Figure 4 shows a grey-level example of the test images of known composition used. The test images were scripting samples using both upper and lower case letters, produced by four different scribes. A total of 192 test images of known ink composition were produced (4 scribes x 8 inks x 3 pens). In addition four images (Figure 5,) from Byzantine and Post-Byzantine manuscripts were used to test the models.

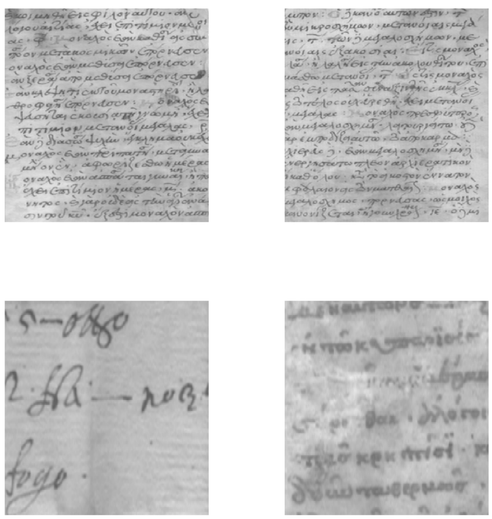

Figure 5. Manuscript images.

3 Analysis

Ink images were examined in the areas with thick layers of ink to overcome the problem of any "noise" introduced by the composition of the support. The segmentation of images can be done using fast Fourier transforms which gives results related to the changing contrast of an image, consequently, these transforms are suitable for our requirements. Using FFTs, band-pass filters were created which select frequencies within certain ranges, thus enabling the areas with the greatest amount of ink to be located.

3.1 Grey-level images

Mixture models were created in the isolated areas of images (Figure 6) in order to characterize ink areas as well as possible. Gaussian mixture models of an ink are parametric statistical models which assume that the ink data consists of a weighted sum of basic ink model components. In this approach, each pixel in the model ink is obtained by selecting the lth component of the model as a density in optical feature vector space that consists of a set of M Gaussian models. Expectation Maximization (EM) is a widely used method for estimating parameter sets of models. With M distributions for each ink, refined models can be created resulting in a more real and accurate characterization.

Inks in test images are classified using Bayes' theorem expressed as:

$$P(\omega_i/x) = \frac{p(x/\omega_i)P(\omega_i)}{p(x)}$$

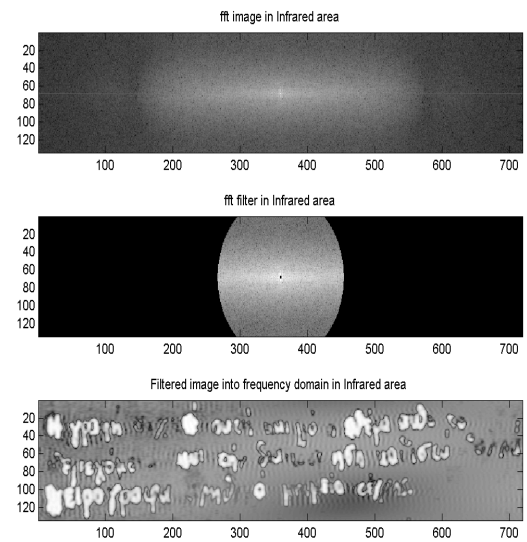

Figure 6. Fast Fourier filter.

where $p(x/\omega_i)$ is the class-conditional probability of ink pixels of test images in relation to inks in model images, $P(\omega_i)$ is the prior probability of model inks and $p(x)$ plays the role of a normalization factor and ensures that posterior probabilities sum to unity. The class-conditional probability is given by:

$$p(x/\omega_i) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(\alpha-\mu)^2}{2\sigma^2}}$$

Where σ is the standard deviation of the model ink, μ is the mean, and α is the pixel value of the test ink.

The normalization factor is obtained as:

$$p(x) = \sum_{j=1}^{n} p(x/\omega_i)P(\omega_i)$$

where n is the categories of model inks.

On E examining the Gaussian mixture models shown in Figure 2 we observe that the large weighted component in all inks includes grey levels of high intensity values. This is consistent with our findings that inks can be most readily differentiated in thick layers of ink where the intensity is low. They also exhibit similar intensities in thin layers due to transparency. Scripting includes a combination of thin and thick layers and therefore it is likely that the areas of low intensity values will provide more information for differentiation. This is overcome when we take into account the likelihood of each intensity value to occur in an ink compared to the overall occurrence of this value in the manuscript inks.

An example is presented in Figure 7 which shows the likelihood results for scripts in irongall ink, written using three types of pen (quill, calamus, penna) and in small or capital letters. On the x-axis, the eight inks in ten different layers (1-80) are listed and on the y-axis the probability value of the ink. The graph shows that five of the scripts were identified as written with irongall ink (the 10 layers of irongall are represented 51-60 on the x-axis) whereas one of the inks in the script is identified as type A.

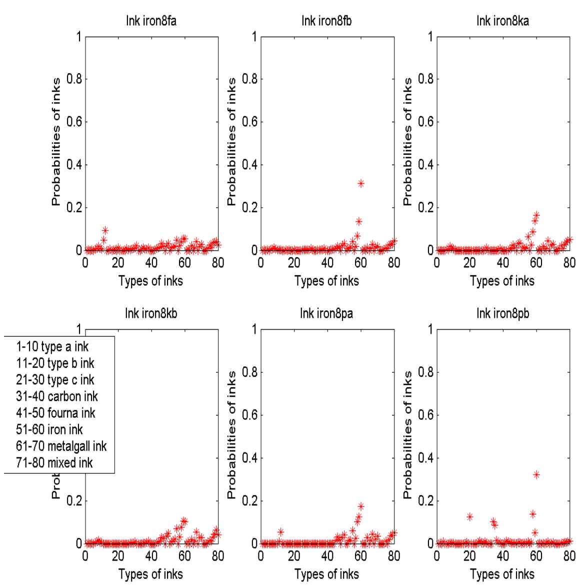

Figure 7. Likelihoods of scripts written in irongall, using 3 types of pen (quill, calamus, penna) in small or capital letters.

3.2 Color images

In the case of color images, we computed the HSV values in isolated areas. These isolated areas were created using band-pass filters to find areas where the amount of ink is a maximum. The EM algorithm was then used to segment these areas of ink from the background. We observed that inks have similar hue values because they have similar color. Only one ink, type A, can be differentiated based on hue values. However, differences among saturation values of inks are observed, and the likelihood of the presence of each ink based on saturation values can be calculated using Bayes' decision rule.

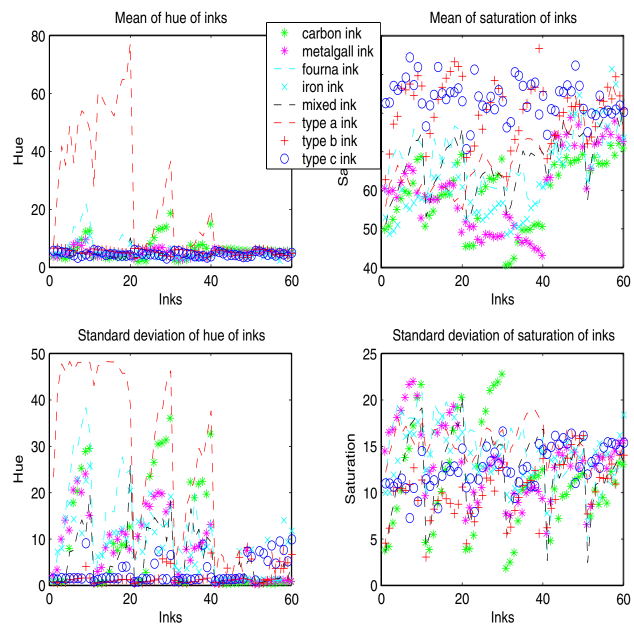

Figure 8. The mean and standard deviation values for Hue and Saturation measurements for the inks.

3.2.1 Saturation values of inks

By studying the saturation values of various types of inks, it is possible to confirm that they can be used as a discriminatory factor. An example of the comparison between the model inks and one of the images that contributed to the models is shown in Figure 9. The image is a script, written with ink type B, using three different pens with small and capital letters. Each graph represents the likelihood of the ink used in the script compared to the model inks. On the x-axis are listed the eight inks in ten different layers and on the y-axis the probabilities of the ink in question. The graph shows that the ink is correctly identified as type B (11-20).

3.3 Comparison of Inks

In order to verify the validity of our approach, the probability classification of the ink model is compared with:

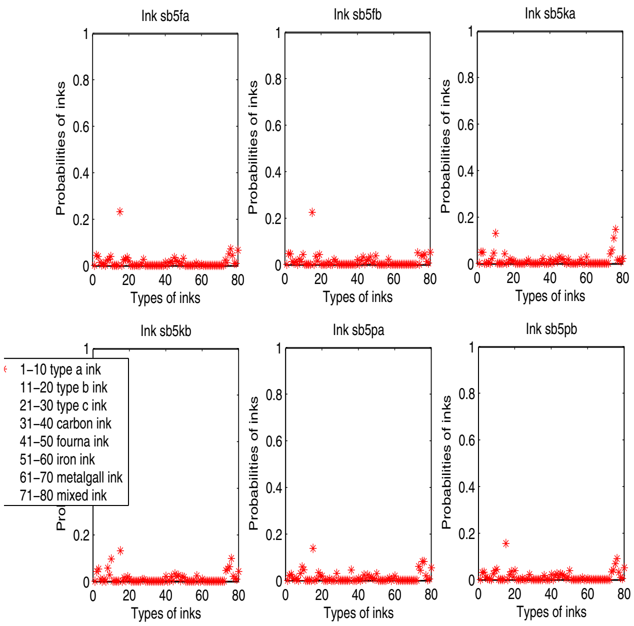

Figure 9. The likelihood of type B ink based on saturation information

- Each of the images that contribute to the creation of the models. The computation of the model of each ink includes 6 images (3 pens x 2 letter cases).
- The test scripting images that are created by different scribes.
- Images of unknown ink composition taken from the manuscripts.

Using the probability classification of inks gave important results

in our attempts to characterize manuscript inks. The results show in most cases that the identification of inks is feasible. The results fall into three categories:

- *Successful*: A result is to be considered as successful when the correct model ink is identified.
- *Screening*: A result is to be considered as screening when the correct model ink is included among the first three results.
- *Unsuccessful*: A result is to be considered as unsuccessful when the correct model ink is not included among the first three results.

Furthermore, in the case of grey level images, a threshold value of 0.05 was used and for color images a threshold value of 0.15, in order to measure the strength of the results given by the estimated likelihood of test inks. The threshold value is the distance between the identified model ink and the other remaining evaluated models. Any probability above 0.05 and 0.15 indicates a strong certainly that the model ink recognized is the correct one, whereas any value below 0.05 and 0.15 indicates a weaker certainty in the results.

4 Results

4.1 Model images

4.1.1 Grey-level images

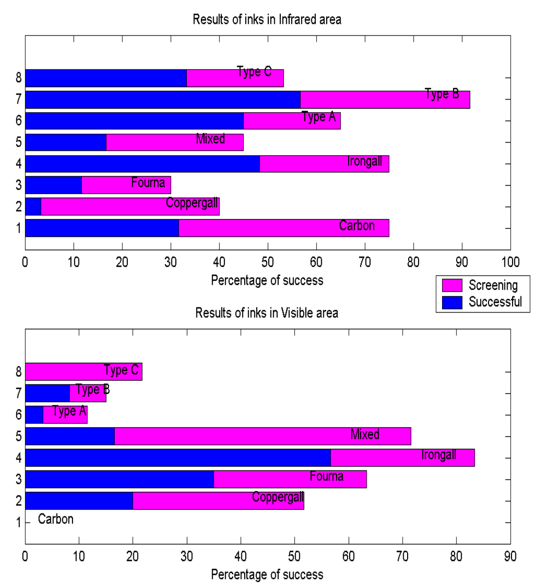

Figure 10. Estimated likelihood based on intensity values.

Figure 10 shows the percentage of the *successful* and *screening* results when the inks models are tested against images that were incorporated in the computation of the model inks. The results are based on the computation of the ink probabilities under visible and infrared radiation. The following is observed:

- All inks were successful and screened in the visible and infrared regions.
- Irongall ink was successful and screened in both regions. The corresponding results being 75% for the infrared and 83.4% for the visible.

- TypeA, typeB, typeC and carbon inks were successful and screened in the infrared only, their results being 65%, 91.7%, 53.3% and 75% respectively.

- Coppergall, Fourna's and mixed inks were successful and screened in the visible only. The corresponding successful and screening results for these inks are 51.7%, 63.3%, 71.6% respectively.

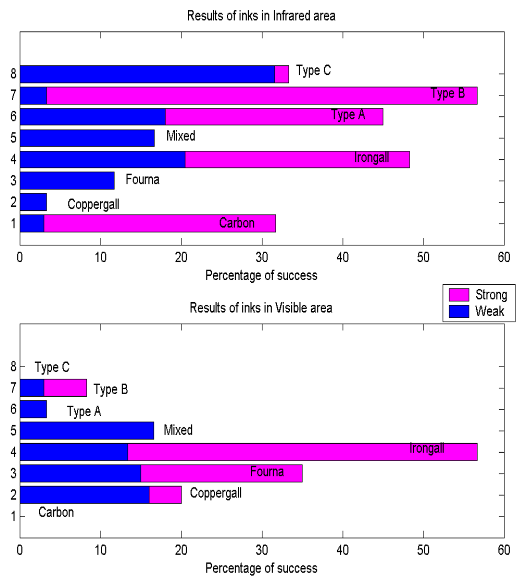

Figure 11. Success estimations based on grey-level values.

The strength, the difference in probability for a given ink, was also computed in order to determine the accuracy of the method. Figure 11 shows the percentage of successful identified models above the threshold value of 0.05(strong results) and the percentage of the correct identified models below the threshold value(weak results). Considering Figure 11 we can make the following comments:

- More successful results occurred in the infrared which suggests that these results are reliable. In the visible the percentage of strong results is low. Only Fourna's and irongall inks have strong results in this region.

- Irongall ink presents a high percentage of strong results in both regions.

- TypeA, typeB and carbon inks offer a high percentage of strong results in the infrared. The smallest percentage of strong results are presented by typeC, mixed and coppergall inks.

- Fourna's ink displays a high percentage of strong results in the visible; it displays a high percentage of weak, and therefore unsuccessful, results in the infrared.

4.1.2 Color images

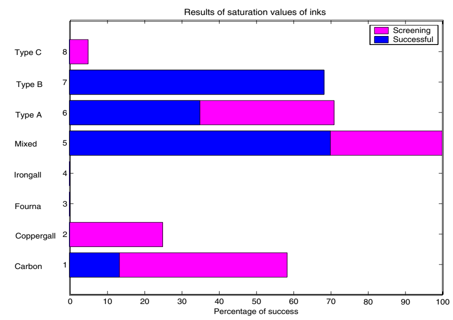

Figure 12. Estimated likelihood based on saturation values.

Inks models are tested against images incorporated in the computation of the model inks. Figure 12 presents the following results:

1. Mixed and typeB inks were successfully identified in 68% of cases.

2. TypeA and carbon inks provided successful and screening results in 58% of cases.

3. Coppergall, typeC, irongall and Fourna's inks were not successful or screened using this analysis.

We also computed the strength of the results above in order to determine the accuracy of the method. Figure 13 shows the percentage of successful identified models above the threshold value of 0.15 (strong results). More of successful results occurred in the infrared suggesting they are reliable.

4.2 Test images

4.2.1 Grey-level images

Figure 14 shows the results of the scripting test images in the infrared and visible, prepared by four different scribes. Examination of the results shows that the classification of most inks was possible. In particular:

- TypeB, irongall, Fourna's and coppergall inks can be successful and screened in both the infrared and visible.

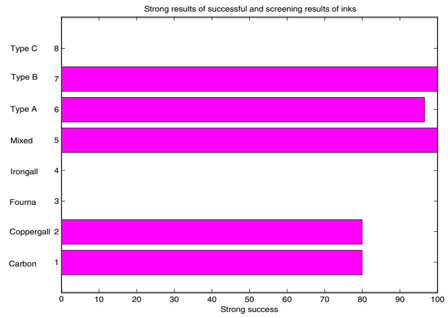

Figure 13. Certainty estimation for likelihood based on saturation values.

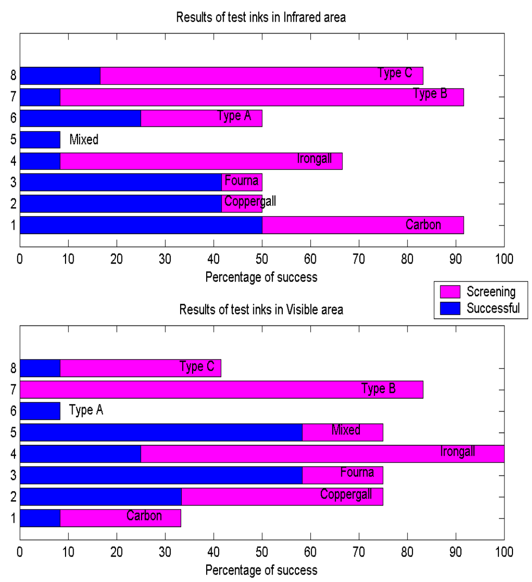

Figure 14. Estimated likelihood of test inks based on saturation values.

- TypeC, typeA and carbon inks can be identified and screened only in the infrared.

- Mixed ink can be identified and screened only in the visible.

The ink models were also tested against Byzantine and Post-Byzantine manuscripts of unknown ink composition. The image based analysis of the manuscripts were compared with the results of the XRF method. Figure 15 and table1 give the results. These show that the composition of the inks used in the four manuscripts can be determined by the probability estimation image-based results. In particular:

Manuscripts	XRF	image-based
Memosa	Fe	TypeA
Memosaa	Fe	TypeA
Memosb	Fe and Cu	Carbon, TypeC, Coppergall
Memosc	Fe and Cu	TypeC and TypeB

Table 1. Comparison between XRF and image-based results on the manuscripts.

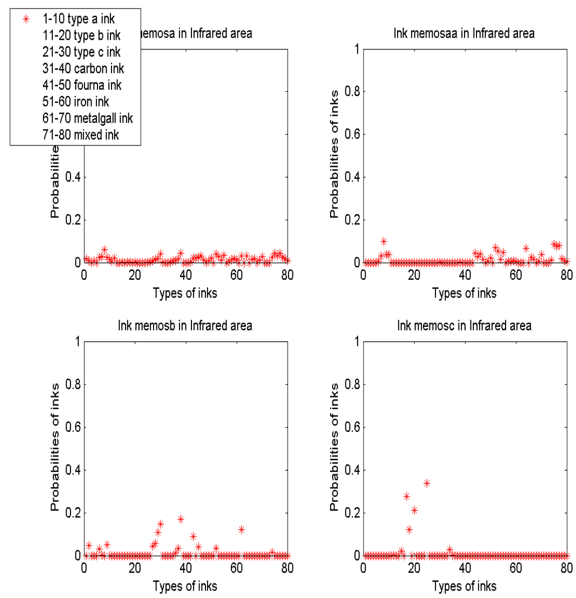

Figure 15. Estimated likelihood of manuscripts based on intensity values

- TypeA inks which have been identified as the correct models for the manuscripts *memosa* and *memosaa* include iron in their composition as confirmed by XRF measurements.

- TypeC and Coppergall inks which have been identified as the correct models for manuscript *memosb* include copper in their composition as confirmed by XRF measurements. Carbon ink which has been found in *memosb* using image-based analysis, was not detected by XRF measurements.

- TypeC ink which models as the correct ink of manuscript *memosc* includes copper in its composition as verified by the XRF measurements for this manuscript.

4.2.2 Color images

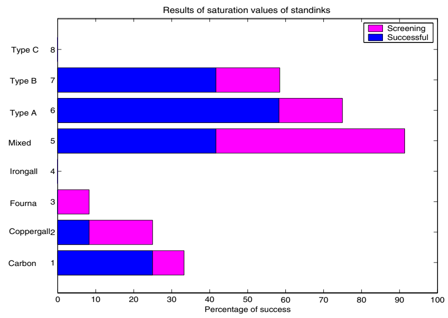

Figure 16. Estimated likelihood of test images based on saturation values

Figure 16 shows the results of the scripting test images. Consideration of these results leads to the following conclusions:

1. Mixed, typeA, and typeB inks can be successful and screened, based on the saturation value of ink pixels.

2. Carbon, coppergall, Fourna's, irongall and typeC inks cannot be identified.

The image based results of authentic manuscripts of unknown composition, were compared with the results of later analysis by the XRF method. Figure 17 gives the saturation probability of ink pixels for the four manuscripts.

The comparison is given in table2 which shows that:

- Mixed, Fourna's and typeB inks found in *memosa* using the saturation probability image-based analysis were not detected by XRF measurements.

- TypeB and mixed inks were found in *memosaa* with the saturation probability image-based analysis, were not detected in manuscript inks by XRF measurements.

- The saturation probability image-based analysis indicated that the inks employed for *memosb* and *memosc* can be identified with the model mixed ink. The XRF measurements showed that *memosb* and *memosc* contained copper in their composition. The typeB ink found for *memosb* and *memosc* using the saturation probability image-based analysis, was not detected by XRF measurements. The same happens for Fourna's ink which was found to be the correct model for the ink of manuscript *memosc* and includes in its composition copper, as validated by XRF measurements.

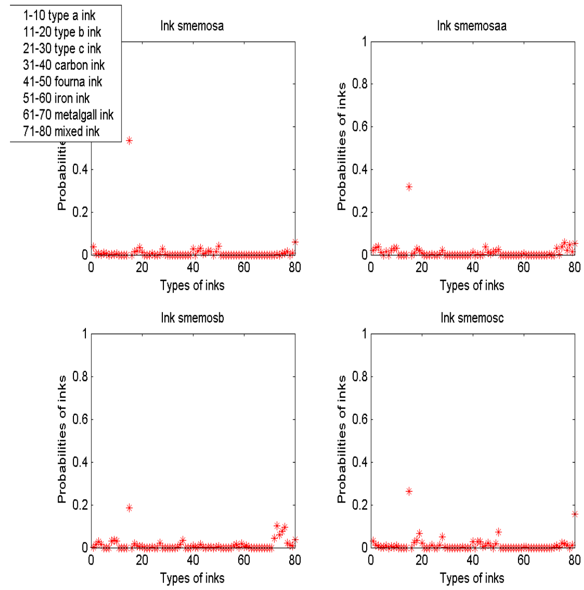

Figure 17. Estimated likelihood of manuscripts based on saturation values.

Manuscripts	XRF	saturation probability image-based
Memosa	Fe	TypeB, Mixed, Fourna's
Memosaa	Fe	TypeB, Mixed
Memosb	Fe and Cu	TypeB, Mixed
Memosc	Fe and Cu	TypeB, Mixed, Fourna's

Table 2. Comparison between XRF and the saturation probability image-based results on the manuscripts.

5 Conclusions

The methodology of this study is based on the probability classification of ink pixels through a mixture of Gaussian models of diverse types of inks. Analysis in the visible region of the spectrum mainly reflects the ink intensity, whereas analysis in the infrared reflects the ink composition. Analysis of color images reflects the color characteristics of various types of inks. We have taken into account scripting with different pens, scribes and the thickness of the inks in our experiments.

Based on the results presented we conclude that statistical analysis and classification based on Bayes' decision rule can provide reliable information towards the identification of manuscript inks when intensity values are used. Results are not yet clear when saturation values are used. Whilst the probability classification was successful or screened for all inks in this study, further work is underway to combine these results with additional characteristics of the behavior of the inks during the scripting process together with more in depth analysis of the effects of substrates.

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References

[1] Alexopoulou A. ,Kokla V. *Physicochemical study of inks of manuscripts using ultraviolet and near infrared radiation*. 6th International Conference on Non-Destructive Testing and Microanalysis for the Diagnostics and Conservation of the Cultural and Environmental Heritage, 1999, vol. 2, pp. 2047-2056.

[2] Barrow W.J. *Manuscripts and Documents*. University Press of Virginia, edition 2nd, 1972.

[3] Clark M. *Anglo-Saxon manuscript pigments*. Studies in Conservation,Vol. 49, no 4, 2004, pp. 231-244.

[4] Delaney J.K., Metzger C., Walmsley E. *Examination of the Visibility of Underdrawing Lines as a Function of Wavelength*. ICOM Committee for Conservation, 10th Triennial Meeting, Washington, 1993, pp. 15-19.

[5] De Pas M. *Etat des travaux effectues sur l' analyse des consititues des encres noires manuscripts par deux technique: chromatographie sur couche mince et electrophorese*. Comite pour la conservation de l' ICOM, 1975.

[6] Derrick R. Michele, Stulik Dusan, Landry M. James. *Infrared Spectroscopy in Conservation Science*. The Getty Conservation Institute, Los Angeles, 1999.

[7] Emmel P., Hersch R. D. *Spectral Color Prediction Model for a Transparent Fluorescent Ink on Paper*. IS&T/SID 6th Color Imaging Conference: Color Science, Systems and Applications, USA, 1998, pp. 116-122.

[8] Fletcher S. *A Preliminary Study of the Use of Infrared Reflectography in the Examination of Works of Art on Paper*. ICOM Committee for Conservation, 7th Triennial Meeting Preprints, Copenhagen, (1984), 84, 14, pp.24-27.

[9] Flieder F., Barroso R., Orvezabal C. *Analysis des tannins hydrolysable susceptibles d' entrer dans la composition des encres ferro-geliques*. 1975.

[10] Fossier L. and Irigoin J. *Dechiffrer les ecritures effacees*. Centre National de la Research Scientifique, Paris, 1990.

[11] Fuchs R. and Oltrogge D. *Modern scientific manuscript research and conservation*. in Fellows-Jensen G. and Springborg P., eds, Care and conservation of manuscripts 3: Proccedings of third international seminar on the care and conservation of manuscripts held at the University of Copenhagen 14th-15th October 1996, The Royal Library, Copenhagen, 1997, pp. 77-98.

[12] Gevers, T. and Smeulders, A. *A comparative study of several color models for color image invariant retrieval*. Proc of First Int. Workshop on Image Databases and Multimedia Search, pp 17-27, Amsterdam, August, 1996.

[13] Granado I. *Automatic feature extraction on pages of antique books through a mathematical morphology based methodology*. Actas de 10EPCG-10 Encontro Portugues de Computacao Grafica, Lisboa, Portugal, 2001, pp. 115-122.

[14] Hanbury A., Kammerer P., Zolda E. *Painting Crack Elimination Using Viscous Morphological Reconstruction*. 12th International Conference on Image Analysis and Processing(ICIAP'03), (2003), Mantova, Italy p.226.

[15] Janssens, K. *Use of Micropscopic XRF for Non-destructive Analysis in Art and Archaeometry*. X-Ray Spectrometry 29, 73-91, 2000.

[16] Kossolapov A.J. *An Improved Vidicon TV Camera of IR-Reflectography*. ICOM Committee for Conservation 10th Triennial meeting, International Council of Museums, Washington, 1993, pp. 25-31.

[17] Niblack, W., Barber, R., Equitz, W., Flickner M., Glassman, E., Petkovic D. and Yanker, P. *The QBIC project: Querying images by content using color, texture and shape*. In SPIE 1908, Storage and Retrieval for Image and Video Databases, February, 1993.

[18] Pappas M., and Pitas I. *Old painting digital color restoration*. in Proc. Of Noblesse Workshop on non-linear model based image analysis", p. 188-192, Glasgow, July, 1998.

[19] Pappas M., and Pitas I. *Digital Color Restoration of Old Painting*. IEEE Transactions on image processing, Vol. 9, No. 2, 2000.

[20] Rossi M., Casali F., Casadei G., Zuelli S. *Image Reconstruction of Painting Radiographs*. 6th International Conference on Non-Destructive Testing and Microanalysis for the Diagnostics and Conservation of the Cultural and Environmental Heritage, Ministry of Cultural Heritage and Activity Central Institute for Restoration (I.C.R.) and Italian Society for Non-Destructive Testing Monitoring Diagnostics (AIPnD), Rome, (1999), 1077-1086.

[21] Smith, J.R. and Chang, S.F. *VisualSEEk: A fully automated content-based image query system. ACM Multimedia*. Bonston, MA, November 1996.

[22] Walmsley E., Flecher C., and Delaney J. *Evaluation of System Performance of Near-Infrared Imaging Devices*. Studies in Conservation 37, 1991, pp. 120-31.

[23] Walmsley E.,Metzger C., Flecher C. et al. *Evaluation of Platinum Silicide Cameras for Use in Infrared Reflectography*. ICOM Committee for Conservation 10th Triennial meeting, International Council of Museums, Washington, 1993, pp. 57-62.

[24] Xiangyang L., Dongming L., Yunhe P. *Color Restoration and Image Retrieval Techniques for Dunhuang Fresco Preservation*. IEEE Multimedia,April-June, 2000, pp. 38-41.

[25] Zerdoun Bat-Yeouda M. *Les encres noires au moyen ages(jusqu' a 1600)*. edition du CNRS, 1983.

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