https://doi.org/10.2352/issn.2168-3204.2025.22.1.3

Adaptive combined method for material identification in documents of historical interest

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Abstract

Hyperspectral imaging has been widely and consistently applied in the field of Cultural Heritage for material identification. In the specific context of historical document analysis, it is frequently supported and complemented by additional analytical techniques. In this study, we propose a straightforward method for material identification that combines adaptive direct identification—using a reference library of visible and near-infrared spectral reflectance data for pigments—with a KNN classifier applied to an extended spectral range for inks and supports. The method has demonstrated a high degree of accuracy, successfully identifying materials present in both actual historical documents and mock-ups created following medieval techniques. Its performance is illustrated through three spectral image fragments extracted from the HYPERDOC project database.

Introduction

Hyperspectral Imaging (HSI) has been consistently applied over the past 30 years for material identification in Cultural Heritage [1–4], although its use has been comparatively less frequent in the analysis of historical documents [5–7]. For conservators and archivists, the ability to identify the materials used in the production of such documents is of considerable importance. HSI has emerged as a desirable technique in this context due to its capacity for on-site measurements (portability), its non-invasive nature and its relatively fast acquisition, especially when compared to point-based techniques [8]. The range of pigments, dyes, inks and supports found in historical documents is generally limited by practical constraints related to Illumination methods and the availability of materials at a given place and time. This means that material identification in this context is not expected to be as complex as in other Cultural Heritage domains. However, variations in the recipes used for material preparation and the natural ageing of the materials can cause significant changes in their spectral reflectance, potentially leading to misclassification [9], even when classifiers are trained with samples from actual historical documents. One of the main objectives of the HYPERDOC project, led by the Color Imaging Lab of the University of Granada, is to provide useful datasets and analysis tools for material identification in historical documents based on HSI data. A first step towards this goal has been the launch of the HYPERDOC Database in February 2025 [10], which includes 1681 fragments of spectral images comprising over 1100 fragments of mock-ups produced using medieval techniques on handcrafted supports, and more than 500 fragments from real historical documents preserved in the Archives of the Royal Chancellery of Granada, the Provincial Historical Archive of Granada and the Alhambra Archives. The dataset has been well received, with over 45 researchers granted access to date, and it can be used to train models for material classification, with promising results already obtained using Support Vector Machines and Deep Learning-based approaches [11]. However, handling such a large volume of data for model training can be complex or impractical in certain cases. In this work, we present a relatively simple strategy for material identification using visible and near-infrared (VNIR) spectral reflectance data and a colour-based adaptive direct identification method relying on a reference library of spectra for various pigments, dyes, inks and supports. Since this method alone was not sufficient for accurate identification of inks and supports, it is complemented by a k-nearest neighbours (k-NN) classifier developed in [11] for inks and here extended to supports, using additional data from the short-wave infrared (SWIR) range. To demonstrate the potential of this combined method, three different fragments (minicubes) from the HYPERDOC database are analysed, and the method is able to correctly identify all materials present in each fragment in under one minute. A detailed description of the method, the results obtained and a discussion of its main limitations are presented in the following sections, and the method will be incorporated in the coming months into the analytical tool (HYPERDOC tool) that constitutes the second deliverable of the project.

Materials and Methods

Materials

The hyperspectral image fragments analysed in this study have been extracted from the HYPERDOC project database [10] and correspond to two historical documents from the Archive of the Royal Chancellery of Granada (minicubes 1 and 2), and one mock-up sample containing a superimposed mixture of materials (minicube 3). The two historical documents are Royal Executory Provisions of Nobility Status, dated 13th February 1539 and 24th September 1587, respectively. False RGB images of the selected fragments are shown in Figure 1.

***Figure 1**. False RGB images ([605, 535, 430] nm bands) of the 3 minicubes of the HYPERDOC database used in this study. Left: minicube 1; Capital letter and text from the document dated on 1539 (124x108 pixels); middle:minicube 2; handwritten text from the document dated 1587 (111x65 pixels); right: minicube 3; mock-up sample with mixture of two pigments by superposition (196x81 pixels).*

The support material for both historical document minicubes is parchment. In minicube 1, the main materials present are cinnabar and Verdigris/malachite in the capital letter, and iron gall ink in the body of the text. In minicube 2, the text is handwritten using iron gall ink. In minicube 3 (mock-up), a superimposed mixture of malachite and lead white bound with egg white has been deposited on a cotton–linen handcrafted paper support produced by the Paperlan company (Asturias, Spain). The materials in minicubes 1 and 2 have been identified by X-Ray Fluorescence (for pigments and inks), with additional confirmation of the support material provided by a conservator's expertise.

Methods

Spectral capture

The line-scan camera Pika L (Resonon Ltd.) was used for spectral acquisition in the visible and near-infrared (VNIR) range, covering wavelengths from 400 to 1000 nm, with a spatial resolution of 900 pixels per line and a spectral resolution of 2.1 nm. Spectral binning was applied, and the resulting data were interpolated with a 5 nm sampling interval, yielding 121 spectral bands. The documents were placed on a motorized linear stage under halogen illumination, with a capture distance of 60 cm, which resulted in a spatial resolution of approximately 150 μm/pixel. As part of the HYPERDOC dataset, the images were also acquired using a Pika IR+ line-scan camera (Resonon Ltd.) operating in the short-wave infrared (SWIR) range, from 900 to 1700 nm. The SWIR data are only used in the third step of the identification algorithm.

Reference Library

A reference spectral library consisting of 45 spectra was constructed using mock-up data available in the HYPERDOC database. The spectra were obtained by averaging the reflectance of a 30×30 pixel region of interest containing the material, in both the VNIR and SWIR ranges. The two spectral ranges were concatenated by low-level data fusion, after discarding the overlapping end of the VNIR range and the beginning of the SWIR range. This resulted in a unified reflectance spectrum for each material, composed of the first 111 bands of the VNIR range (400–950 nm) and the last 150 bands of the SWIR range (955–1700 nm). The reference library includes 32 pigments and dyes bound with either egg white and/or gum arabic on parchment support. The pigments and dyes are: azurite, buckthorn berry green, burnt umber, calcite white, carmine, cinnabar, gamboge, hematite red, indigo, imperial yellow ink, lapis lazuli, lead tin yellow, lead white, minium, malachite, yellow ochre, orpiment, saffron, smalt and verdigris. The buckthorn berry dye is included in liquid form without binder, and some colorants are bound with only one of the binders (mainly gum arabic). All pigments and dyes were sourced from Kremer Pigmente GmbH (Germany). Eight different inks on parchment support were also incorporated: sepia, lampblack, iron gall, bone black, ivory black, cherry black, grape black and bistre. In addition, five different supports were included: parchment from Römer Shop (Glasburg, Germany), cotton–linen paper, linen paper, cotton paper from Paperlan (Gijón, Spain), and hemp paper from Wanderings Inc. The spectra in the reference library were grouped into seven subsets. Five of them contain only pigments and dyes and are categorized by perceived colour (BLUE, GREEN, RED, YELLOW, ORANGE). The remaining two subsets contain the ink (INK) and support (SUPPORT) samples, respectively.

Material identification method

The material identification method is structured in three steps: superpixel segmentation, adaptive colour group-based material voting by superpixel, and refinement of the results for inks and supports using a KNN-based classifier.

The first step (superpixel segmentation) aims to reduce the number of spectra in the hyperspectral image by grouping similar pixels into spatial subsets called superpixels. Superpixel segmentation is widely used in image processing, and in this work the algorithm proposed by Achanta et al. [12] is applied. The over-segmentation is performed on the false-colour RGB image and then transferred to the hyperspectral image. The number of superpixels generated ranges from 5995 to 6820 per fragment, with an initial superpixel number set to 7000 in the algorithm parameters. After segmentation, the spectra of all pixels within each superpixel are averaged to reduce data volume.

The second step (adaptive colour group-based material voting) consists of two sub-procedures: colour group assignment and adaptive material voting. The colour group assignment requires a predefined number of colour groups in the image and a representative spectrum for each group. These groups are defined by visual inspection of the images, and a 3×3 pixel region of interest is manually selected and averaged to obtain the representative spectrum for each group. These spectra are then compared to the average spectrum of each superpixel, and the colour group is assigned based on the representative with the minimum distance. The distance metric is a combination of three components: the

CIEDE00 colour difference [13], the root mean square error (RMSE), and the complementary Goodness-of-Fit Coefficient cGFC=1−GFC [14], as defined in equation (1).

$$CM_1 = \Delta E_{00} + 0.25 \cdot RMSE + 0.25 \cdot cGFC \qquad (1)$$

As an example, four colour groups are considered for minicube 1: RED, GREEN, INK and SUPPORT. For minicube 2, only INK and SUPPORT are present, while minicube 3 includes GREEN, WHITE and SUPPORT.

The second procedure within this step is adaptive material voting. Each superpixel votes for a candidate material among the reference spectra contained in its assigned colour group (adaptive voting). The selected material is the one that minimises the combined distance according to the metric defined in equation (2), as introduced in Valero et al. (2023) [4].

$$\mathrm{CM}_2 = 0.02 \cdot \Delta \mathrm{E}_{00} + \mathrm{RMSE} + 0.5 \cdot \mathrm{cGFC} \qquad (2)$$

Eqs. (1) and (2) differ in the weights assigned to each metric. In the colour group assignation, more weight is given to the color difference metric, while for material identification, more weight is given to the spectral metrics. The second step allows for the generation of voting maps to visually summarise the results. In these maps (see Figure 3), superpixels that voted for a given colour group or material are displayed in their corresponding RGB value, while the remaining areas of the image are shown in white [255,255,255].

The third and final step is the refinement of the ink and support classification using two k-NN-based classifiers, each relying on an extensive reference dataset of ink and substrate spectra extracted from the HYPERDOC database. These reference spectra include the short-wave infrared (SWIR) range from 900 to 1700 nm, which is known to be particularly relevant for ink and support identification [11]. The k-NN classifier for inks uses 751267 reference spectra and applies the cosine distance metric to distinguish among three ink classes: metallo-gallate pure, carbon-containing, and non-carbon-containing. The k-NN classifier for substrates differentiates between parchment, cotton–linen, linen and cotton papers, using a total of 2038511 reference spectra and the cityblock distance metric, which worked better than cosine distance according to preliminary trials. Both use k=1 as number of neighbours. This final step is necessary because we observed that the results from adaptive material identification were generally less accurate for the INK and SUPPORT groups. This is due to the considerable variability in the spectral characteristics of inks and supports, influenced by differences in manufacturing conditions, recipes and natural ageing processes. As a result, using only one representative instance per material was insufficient for these two categories, whereas it was typically effective for pigment identification. Figure 2 illustrates the main steps of the proposed method.

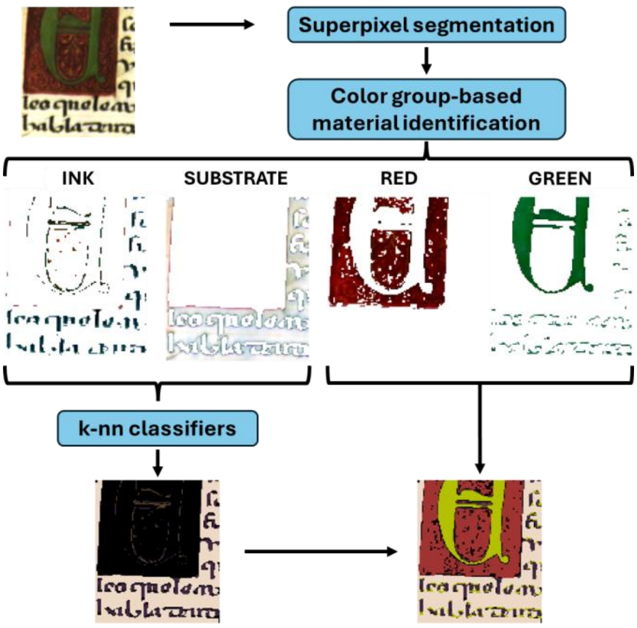

Figure 2. *Workflow illustrating the steps of the proposed method.*

Results

First step: superpixel segmentation

The superpixel segmentation yielded a total of 6424 superpixels for minicube 1, 5914 for minicube 2 and 5802 for minicube 3. The corresponding reduction in the number of spectra ranged from 18.03% to 65.45%, with most superpixels comprising only one or two pixels. Despite the relatively small size of many superpixels, this reduction is significant as it contributes to a noticeable decrease in computation time during the subsequent processing steps.

Second step: subset-based adaptive material voting

The first part of this step is the color group assignation. As explained in the previous section, each pixel is assigned to a color group depending on its spectral and color proximity to a manually extracted set of representative spectra. There is one representative spectrum for each of the a priori determined color groups present in the minicube. Once the assignment is completed, presence maps can be generated to visualise the distribution of each colour group. In these maps, pixels not belonging to the selected group are displayed in white [255,255,255], facilitating the interpretation of the results (see Figure 3).

The colour group assignment generally produced reasonable results, with two notable exceptions. In minicube 1, some ink pixels were incorrectly assigned to the GREEN group, while in minicube 2, some ink pixels were classified as SUPPORT. The first anomaly can be explained by the spectral influence of the parchment support at the edges of the ink strokes, which appear lighter than the central parts. As the GREEN representative was extracted from the dark green capital letter, these lighter ink-edge pixels appear more similar to the dark pigment than to the ink. The second anomaly has a similar cause: the ink representative in minicube 2 was extracted from the centre of a stroke, while the lighter border pixels were spectrally closer to the SUPPORT representative than to the ink.

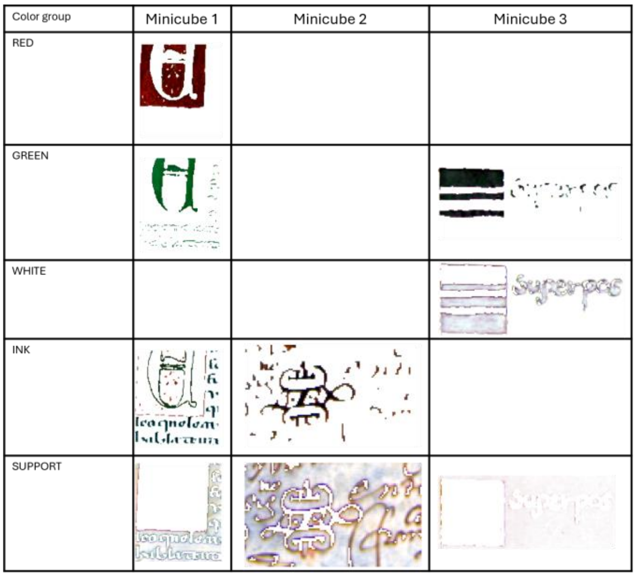

Figure 3. *Presence maps of the color groups pre-defined for each of the three minicubes used in the study*

In the second part of this step, adaptive material identification is carried out by allowing each superpixel to vote for a candidate material within its assigned colour group. The selected material corresponds to the spectrum in the group with the minimum combined distance, according to the metric defined in equation (2) [4]. Presence maps for the most voted materials are shown in Figure 4, together with the percentage of total votes associated with each material.

The pigments were correctly identified in all cases for minicubes 1 and 3. However, misclassifications occurred in the case of inks and supports in minicubes 1 and 2, which are historical documents. In both, the ink was iron gall but was misidentified as ivory black, and the support, which is parchment, was misclassified as linen. In contrast, the support in minicube 3 (cotton-linen paper) was nearly correctly identified as linen instead of cotton-linen paper.

These misclassifications are mainly due to the spectral limitations of the VNIR range used for distance computation in this step. Ink spectra in the VNIR tend to be flat, with low reflectance and few distinctive features, which limits the method's discriminative power for inks. In contrast, pigments typically show clearer spectral differences in this range.

The results were not unanimous within the color groups, with the exception of the INK color group for minicube 2. In minicube 1, the GREEN group showed similar percentage of votes to the ML2 pigment for buckthorn berry dye. A small

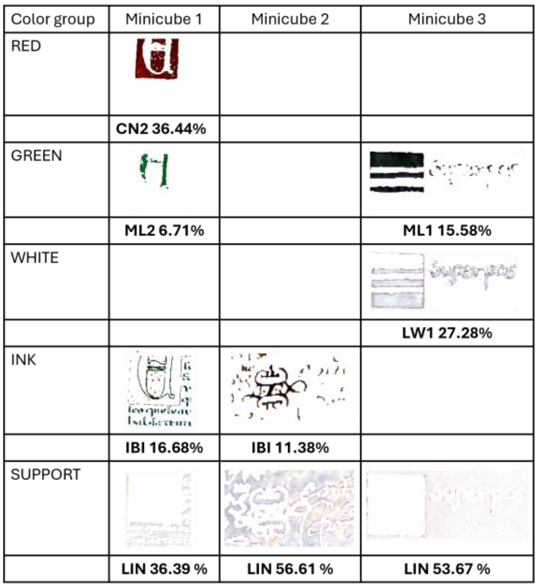

Figure 4. *Presence maps for the most voted materials within each color group of the three minicubes used in the study after step 2.*

number of pixels in the INK group voted for iron gall, and 12.08% of SUPPORT pixels voted for parchment. In minicube 2, the SUPPORT results registered a 28.95% of superpixels voting for parchment (mostly the ink pixels wrongly assigned to this group), while residual amounts voted for cotton, cotton-linen and hemp. In minicube 3, only residual amounts of votes were casted for calcite white and LW2 in the WHITE group and parchment in the SUPPORT color group, indicating clearer identification.

Third step: refinement for ink and support pixels

As previously explained, this final step refines the classification of inks and supports using KNN-based classifiers that operate on concatenated VNIR and SWIR spectra. When applied to the average spectra of the SUPPORT colour groups, the method correctly identified *parchment* for minicubes 1 and 2, and *cotton-linen paper* for minicube 3.

Regarding inks, the classifier correctly identified *pure iron gall ink* in both minicubes 1 and 2. When the KNN classifier is applied on a pixel-by-pixel basis with majority voting for decision-making, the same results are obtained. However, approximately 30% of the SUPPORT group pixels in minicube 3 were identified as parchment, particularly on the right side of the image. In minicube 1, while the text was correctly classified as iron gall, some edge pixels in the capital letter were misclassified as non-carbon-containing ink. Only one pixel of the support was misclassified as linen paper.

Overall, the use of average spectra appears more practical for classification in this context. However, pixel-based classification provides valuable insights into the internal variability of spectral features within each minicube.

Pixel-based hit rate evaluation

The presence maps resulting from Step 3 were compared with Ground Truth (GT) images from the HYPERDOC database to evaluate classification accuracy at the pixel level.

The GT images are color-coded according to the material present in each pixel, and they can be converted into binary presence maps for each material. In these binary maps, the pixels containing the material are shown in white, and the rest of the pixels in black. Comparing the GT binary maps with the results of the pixel-based classification similarly expressed in the form of binary maps (where the pixels classified as containing the material are shown in white and the rest of the pixels in black), the Accuracy, False Positives (FP) and False Negatives (FN) can be obtained.

Table 1 shows the results of this evaluation for the three minicubes analyzed.

Minicube	Material	Accuracy	FP	FN
1	Cinnabar	0.9174	0.0001	0.0824
1	Malaquite	0.9443	0.0000	0.0557
1	Iron Gall Ink	0.8604	0.0156	0.1240
1	Parchment	0.9040	0.0952	0.0007
2	Iron Gall Ink	0.7214	0.0000	0.2786
2	Parchment	0.7310	0.2689	0.0001
3	Malaquite	0.9449	0.0002	0.00549
3	Lead White	0.9346	0.0630	0.0025
3	Cotton-linen paper	0.7955	0.0026	0.2018

Table 1. Results of the comparison of the pixel-based classification results with the GT image.

These results confirm that the method is largely consistent with the ground truth data. Variability is mainly introduced during colour group assignment and by the accuracy of the KNN classifiers. For example, the 12% FN rate for iron gall ink in minicube 1 is due to some edge pixels being assigned to the GREEN or SUPPORT groups. Similarly, the 27% FN for iron gall ink in minicube 2 corresponds to strokes incorrectly labelled as SUPPORT, which contributes to an increased FP rate in the parchment class. In minicube 3, around 20% of the pixels were incorrectly classified as parchment by the pixel-based KNN classifier, highlighting limitations of the third step.

Despite these shortcomings, applying a simple majority voting rule to the classification results led to the correct identification of all materials in the three analysed minicubes..

Conclusions

In this study, selected samples from the HYPERDOC Database have been used to demonstrate the performance of a material identification algorithm based on reducing the number of candidate spectra in the reference library by assigning each superpixel in the document fragment to a predefined colour group. This simple method provides a preliminary material identification in under one minute. Using only VNIR spectral data, it was able to correctly identify the pigments present in the fragments, although it failed to accurately classify inks and supports. However, after a refinement step incorporating the SWIR portion of the spectra and using the average spectra of the superpixels assigned to the INK and SUPPORT groups, all materials present in the three analysed minicubes were correctly identified. These results highlight the potential of combining adaptive strategies with straightforward methodologies.

Even if similar results could be obtained by comparing each superpixel to the entire reference library, a properly implemented adaptive approach will always reduce computation time significantly by limiting the number of comparisons per pixel, at the cost of requiring prior labelling of the reference spectra by colour group. The effectiveness of the method relies on accurate colour group assignment based on manually extracted representative spectra. Although this step is critical and errors in group assignment may compromise later results, the method has shown some tolerance, as demonstrated by the performance on minicube 2, which exhibited the lowest accuracy in group assignment. Future improvements may include automating the extraction and identification of colour groups directly from the spectral image, thereby reducing manual intervention and enabling the analysis of a greater number of samples within reasonable time frames.

A main limitation of the proposed method is its inability to detect pigment or dye mixtures unless specific mixture instances are already included in the reference library. However, this limitation could be addressed by integrating spectral unmixing techniques using automatically extracted endmembers to identify regions containing material mixtures, which represents a promising direction for future development.

Acknowledgements

This work was supported by MCIN/AEI/10.13039/501100011033, by "ERDF A way of making Europe" [grant number PID2021-124446NB-100], by Ministry of Universities (Spain) [grant number FPU2020-05532], and by "ESF Investing in your future" [grant number PRE2022-101352].

We would like to acknowledge David Torres Ibáñez, Director of the Archive of the Royal Chancellery of Granada, and Eva Martín López, Director of the Provincial Historical Archive of Granada, for their assistance.

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Ana López-Montes *received her B. Sc. in Fine Arts with the specialization on Restoration at the University of Granada (Spain) in 2001. In 2006 she was awarded her Doctorate in Fine Arts and in 2015 a second Doctorate in Analytical Chemistry. She carried out her post-doctoral stays in IRAMAT-CNRS (Orléans, France) and in CRC-CNRS (Paris, France). She has worked at the Department of Painting at the University of Granada as Associate Professor from 2019.*