

ANALYSIS OF PAINTINGS USING MULTI-SENSOR DATA

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ABSTRACT

In this work we propose a system for region segmentation of hyperspectral painting images based on pigments identification method and clustering. Our system combines the molecular information (obtained by hyperspectral camera) with the elemental analysis. The data acquired on the paintings are compared with a database of reference materials that belonged to the artist. The use of reference materials turns out to be crucial in overcoming some of the limitations in the interpretation of the reflectance spectra. In addition, our system is able to detect areas of the painting that were done using materials not usual for our artist; this feature may be of great help in forgery detection.

Index Terms— hyperspectral imaging, elemental analysis, Spectra Angle Mapping

1. INTRODUCTION

Amadeo de Souza Cardoso (1887-1918) was one of the most important modernist painters in Portugal. He was rediscovered in the 1950's and very soon the value of his works increased as well as the numbers of forgeries of his artworks. This work is part of the project *Crossing Borders: History, materials and techniques of Portuguese painters (1850-1918)*. The study of Amadeo's artworks started at the time of the editing of his Catalogue Raisonné [1]. In the first part of the project the problem of author attribution was addressed by the analysis of brushstroke patterns using digital image processing [2]. Developing a robust classification system to resolve authentication issues requires, besides the analysis of the brushstroke, the analysis of the materials present on the paintings.

1.1. Problem statement and related works

Imaging spectroscopy consists in the collection of images using narrow spectral bands; from these images it is possible to represent each pixel as a reflectance spectrum. This technique was used for pigment identification in [3, 4]. The interpretation of the reflectance spectra is usually performed by comparing the unknown spectra to a database of reference materi-

als. The absence of a comprehensive and coherent database is one of the main limitations of this analysis [5]. The materials contained in the database must be prepared with techniques and materials as close as possible to the original ones [6]. In the case of painting materials, the particle size of the pigments, the concentration and types of binding medium could influence the shape of the reflectance spectrum [7].

Methods based on chemometric techniques [8] and using the remote sensing software [4] obtained important results in the classification of hyperspectral images. A weakness of these strategies is that endmembers obtained do not necessarily have any physical meaning, and therefore they cannot help in interpreting the materials present in the painting [5].

The interpretation of the spectra obtained from mixture of pigments or materials is challenging. In the *spectra unmixing* [9] method, the measured spectrum of a mixture is decomposed into a collection of constituent spectra. The main limitation of this method concerns the painting mixture, which not always can be considered as a linear sum of pigments spectra [5]. Methods based on Kubelka–Munk theory provided good results [10] but require the measure of a mixture of the pigment with materials whose absorption and scattering coefficients are known.

Few studies have used the combination of hyperspectral image with the Energy Dispersive X-ray Fluorescence (EDXRF) [5]. EDXRF allows to determine the elements present in the painting based on the interaction of the materials with X-rays. Until now the correlation between reflection imaging spectroscopy and EDXRF is performed by the user without an automatic process.

1.2. Contribution

In this work, we propose an algorithm for segmentation of hyperspectral images based on a pigment identification method and clustering (Fig. 1). The identification of the pigments is performed by combining molecular and elemental information obtained by hyperspectral camera and EDXRF, respectively. To avoid the problems that may arise by the use of inconsistent materials, we use a reference database with information on oil paint tubes which belonged to Amadeo. The complementarity of the information intends to overcome the

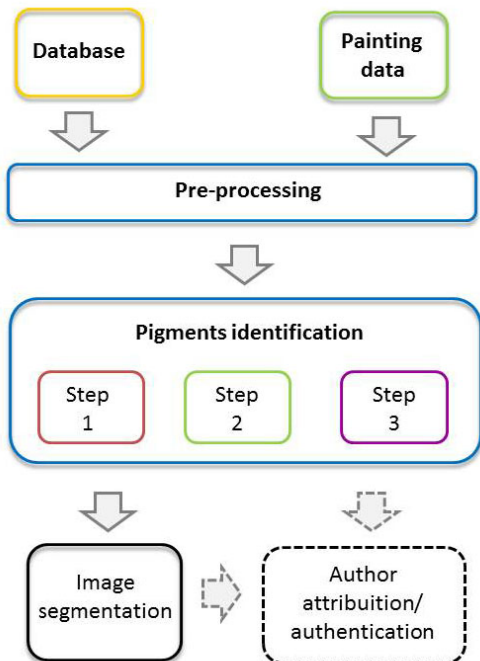


Fig. 1. Block diagram of the proposed method.

limitations of the two techniques and, at the same time, aims to provide a double confirmation of the obtained results.

2. PAINTING ANALYSIS SYSTEM

The method here presented is based on the clustering of the pixels into classes corresponding to predefined training sets—a set of oil paint tubes which belonged to Amadeo. The paintings and the oil paint tubes were analyzed by EDXRF and reflectance spectroscopy.

Spectral Angle Mapper (SAM) and Euclidian Minimum Distance (EMD) are popular metrics for comparing reflectance spectra [3, 11]. In both cases, the spectrum is considered as a vector: EMD measures the distance between the two vectors, while SAM considers the dimension of the angle between them. Unlike SAM [3], EMD is sensitive to the illumination changes; this may provide an excessive number of classes thus making their interpretation quite difficult. We propose a combination of SAM and EMD, inspired on the strategy used by Lowe for matching [12].

The output of the system is an RGB image, where each pixel is classified as belonging to a pigment or mixtures of pigments. To validate the results obtained, the RGB image is compared with those obtained using a method of unsupervised classification based on K-means. Moreover, other spectroscopy analytical techniques were used to confirm the materials identification.

3. INPUT DATA

A set of reference materials (database) and Amadeo’s paintings (paintings data) were analysed using hyperspectral camera and X-ray fluorescence.

3.1. Painting Data

For each analyzed painting, we acquired hyperspectral images (400–720 nm) represented in a matrix $(m \times n \times w)$, where w stands for the 33 values of reflectance over the spectral range. We compute the first derivative for every reflectance spectrum; this process was preceded by a smoothing filter based on the Savitzky–Golay method [13].

The elemental information obtained by EDXRF was introduced manually by the user and it is organized as follows:

$$XRF_{el} = \{el_1, el_2, \dots, el_P\} \quad (1)$$

where P is the number of points where the analysis was performed and $el_P = \{sq_1, sq_2, \dots, sq_K\}$ is the list of the elements detected on the painting.

3.2. Database oil paint tubes

The database used in this work is composed by 15 oil paint tube samples which belonged to Amadeo and produced by two of the many important colormen of the 19th century: Winsor & Newton and Lefranc. The reflectance spectra of these samples were organized as follows:

$$P_{es} = \{es_1, es_2, \dots, es_N\} \quad (2)$$

where N is the number of the reference materials and es_N is the spectra of each reference material of the database. The elementary analysis performed on the paint tubes was organized in the same way as for the paintings data (1).

4. DATA PRE-PROCESSING

Two important data pre-processing techniques were used. The first consists in computing the chromatic values from the reflectance spectra acquired on the painting and on the reference materials. Reflectance spectra can be related to colour using established international conventions developed by the Commission International d’Eclairage (CIE) [7]. From the reflectance spectra it is possible to calculate the tristimulus values (X, Y, Z) , and then define other colour spaces [7]. In this work we used the $L^*a^*b^*$ space.

The second pre-processing technique regards the elemental data; usually for each painting the EDXRF analysis is performed on 15–50 points, depending on the number of colours of the surface. The aim of the pre-processing was to extend the elemental information over the whole surface of the painting. That is, associating each point with the corresponding

chromatic values and later assuming the same elements for all the pixel with the same $L^*a^*b^*$ values:

$$\exists_x \in XRF_{lab} : Lab_i \geq (x - c) \wedge Lab_i \leq (x + c) \quad (3)$$

where c is a constant that defines the interval of colour tolerance. The value of c was chosen in accordance with tests performed on painting areas made with known materials.

5. PIGMENT IDENTIFICATION

This part of the method includes three sequential steps which allow the classification of each pixel of the image according to the material present (Fig. 2).

5.1. Step 1: Area Identification

This step identifies two areas: (i) an area in which EDXRF analysis was not performed (called "No Analysed"). This area covers all the pixels of the hyperspectral image which do not satisfy Eq. 3; (ii) an area painted with pigments that are not included in the database (called "No Amadeo"). This selection is performed by comparing the elements detected in the painting with those present in Amadeo's database. The detection of area (i) avoids performing the classification based on incomplete analytical data, while area (ii) allows to identify pigments introduced in the market after Amadeo's death and that could not be used by him. Those pixels not included in areas "No Analysed" and "No Amadeo" are considered unclassified and will be analyzed in the next step.

5.2. Step 2: Pigment Attribution

In this step each pixel is classified according to its similarity with one of the materials of the database. The similarity between the spectra is calculated using a combination of SAM and EMD and is based on the method of matching proposed by Lowe [12]. First, we compute the angle between the unknown spectrum (*pixel p*) and spectra of each material of the database:

$$\alpha_{p,r} = \cos^{-1} \left[\frac{\sum_{i=1}^n R_{p,i} R_{r,i}}{\sqrt{\sum_{i=1}^n R_{p,i}^2 \sum_{i=1}^n R_{r,i}^2}} \right] \quad (4)$$

Then, we order all the materials by ascending order according to Eq. 4. Finally, pixel p is labeled in with material r_1 if:

$$\alpha_{p,r_1} < \alpha_{p,r_2} \quad (5)$$

where α_{p,r_1} is the lower angle and α_{p,r_2} is the second lower angle. For the unclassified pixels the similarity is re-calculated using EMD:

$$EMD_{p,r} = \sqrt{\sum_{i=1}^n (R_{p,i} - R_{r,i})^2} \quad (6)$$

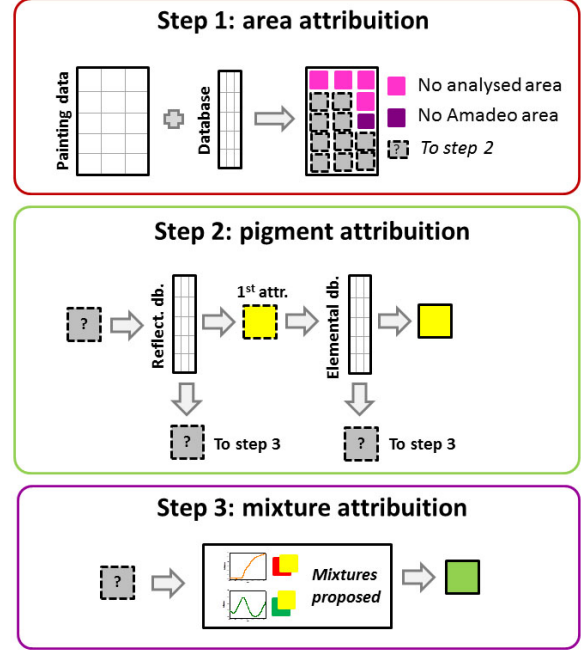


Fig. 2. Steps in pigment identification

The pixel p is labeled with the material r with the lower value obtained by eq. 6.

The pigment attribution obtained after this processing is confirmed by relying on elemental analysis performed on the painting. The algorithm compares the elements that characterize the pigment proposed with the elements detected by EDXRF in the corresponding area on the painting. If the attribution proposed is consistent (i.e., if the element(s) detected on the painting are the same of the pigment proposed) then the pixel is classified according to the given assignment; otherwise, the pixel is defined unclassified and passes to Step 3.

5.3. Step 3: Mixture Identification

Based on the elemental analysis performed on the painting, the algorithm selects from the database the pigments that could be present; from the pigments selected the program calculates all the possible mixtures considering proportions from 100:0 to 50:50 % with increases of 10%. For each mixture, a reflectance spectrum is computed as the linear sum of the spectra of the pigments. These mixtures constitute a new database, that will be used to classify the pixels hitherto unclassified. The similarity between the spectra and the database of mixtures is calculated using SAM (Eq. 4).

5.4. Image segmentation- RGB image

The output of the system consists of an RGB image. The RGB values of each pixel are calculated from the reflectance

spectrum of the pigment or mixture according to which have been classified (Eq.4). The RGB values for the pixels which belong to "No Analysed" and "No Amadeo" areas are freely chosen by the user (Sec.6)

6. RESULTS AND DISCUSSION

Our system was used on eight Amadeo's paintings and two paintings made by the students of Department of Conservation and Restoration (DCR). These last paintings were prepared using current materials as well as pigments present in the Amadeo's palette. Here we present the results obtained on *Mucha*, Amadeo's painting of 1915 and one of those prepared at DCR.

One way to evaluate the results achieved with our system is to compare the segmented image with those obtained with a clustering method. This clustering is based on k-means method, where SAM is used to calculate the spectra angle between each centroid and the pixels of the images. All the calculated angles are sorted by ascending order. If the first and the second angles follow the condition in Eq. 5 then the pixel is included in the cluster corresponding to the first angle. The algorithm produces a segmentation image in which all pixels that belong to the same cluster are visualized with an RGB value that is calculated from the reflectance spectra of the centroid of the cluster.

The first evaluation is based on the results shown in Fig. 3. From Fig. 3(a) and (b) it is evident how the classification based on k-means and SAM is strongly influenced by the number of clusters chosen. The best results were achieved using a number of clusters larger than the numbers of reference materials. That proves the unsuitableness of this method for the extraction of the material information. Fig. 3 (c) and (e) are the RGB images of the paintings analyzed. As we can see, the regions displayed using our method (see Fig. 3 (d) and (f)) are closer to the original than the clustering method. In the segmented images, the pink colour indicates the "No Amadeo" areas and the grey the "No Analysed" areas. As expected, the forgery painting shows a large "No Amadeo" area. That area is quantified in Table 1.

Table 1. Percentage of areas detected on *Mucha* and *DCR* paintings.

Area	Percentage	
	<i>Mucha</i>	DCR painting
No Analysed	4.2	3.5
No Amadeo	0.0	17.3
Amadeo	95.8	79.2

The yellow, orange and red shades (indicated in Fig. 3 (c) with the letters Y, O and R) are painted using different amount of Chrome yellow ($PbCrO_4$) mixed with Vermilion (HgS). Fig. 4 (a) reports an example of reflectance spectrum

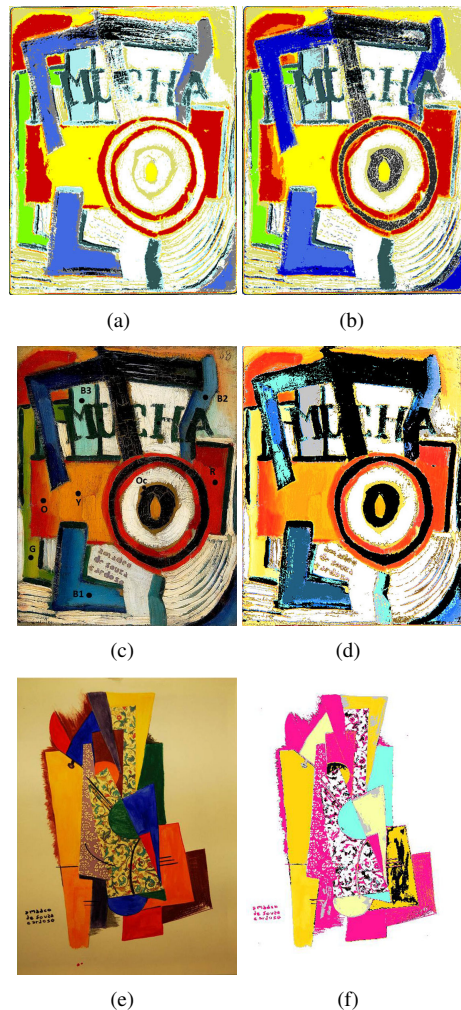


Fig. 3. *Mucha* painting: cluster method using (a) 15 clusters; (b) 70 clusters; (c) original RGB image; (d) segmented image. *DCR* painting: (e) original RGB image; (f) segmented image. In grey the "No Analysed" area and in pink the "No Amadeo".

measured in the area Y and the spectrum computed by our method (Sec. 5.3), which shows a good correlation between them. Chrome yellow is also used in mixture with Viridian ($Cr_2O_3 \cdot H_2O$) to obtain the green tone (area G in Fig. 3 (c)). Both, Chrome yellow and Viridian are characterized by the presence of the element Chromium (Cr) but the reflectance information allows to determine the correct classification of this area.

On the contrary, in the case of the Blue area (Fig. 4(b)) the correlation between the measured and the proposed spectrum is less accurate; this is because Cerulean blue ($CoO \cdot nSnO_2$) and Cobalt blue (CoO) show spectral features very similar to each other. In any case the elemental information guarantees a correct identification of the materials present in the area.

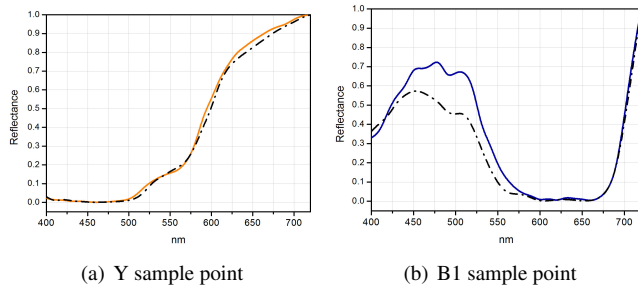


Fig. 4. Measured reflectance spectra (solid lines) and estimated (dot-dashed lines)

7. CONCLUSIONS

Our system performs a classification of the pixels of the hyperspectral image and produces a RGB mapping of the pigment used by the artist. In contrast with the clustering method, the strategy proposed here allows: (i) to define the pigment or mixtures present and (ii) to detect areas that could be not painted by Amadeo. In addition, the results are independent from the chosen number of clusters used. To address the problem of authenticity, it is important to consider several factors; for this reason, we plan to enhance the system here proposed with the brushstroke analysis techniques we have developed in prior work. Also, adapting the proposed system for the study of paintings of other artists is a topic that will be addressed in the future.

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