Color segmentation algorithms to support automatism of graphic documentation in restoration.

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1. Introduction

All the disciplines connected to restoration have always shown a deep need to achieve a wide understanding of the object of interest, in order to develop a greater awareness of the actions needed and to perform in the full respect of its features. This knowledge can only be accomplished through the study of its artistic and conservative history, the techniques and the materials used for its realization. At this cognitive stage, an important role is played by the adaptation in images, texts and graphics of all the information obtained on the artwork. Diagnostic investigation and graphic design are the main tools the restorative operator uses to turn this dialogue into a process of representation where the design acts like a precise language responsible for synthesizing and plainly describing all the information. Several factors contribute to the design's realization, involving theoretical and methodological, based on regulations issued by *Central Institute for Cataloguing and Documentation* [1]. This is the main national authority in Italy for the documentation of restoration activities. On the basis of these regulations, all restoration interventions must be preceded and accompanied by documentation to create a *"medical record"*, so to speak, of the artwork, within which all the collected data are transcribed and archived in different forms, in modalities standardized and geometrically correct [2][3].

Our methodology starts from multispectral imaging coupled with segmentation algorithms for the automatic extraction of regions of interest (ROI) from raster images. Thanks to their different optical behavior, we can isolate different areas of the painting that are attributable to its executive and restoration history. These areas, each corresponding to specific information, are then used for the representation and description of the edge and the area of the regions, producing outputs with vector attributes derived from the raster images.

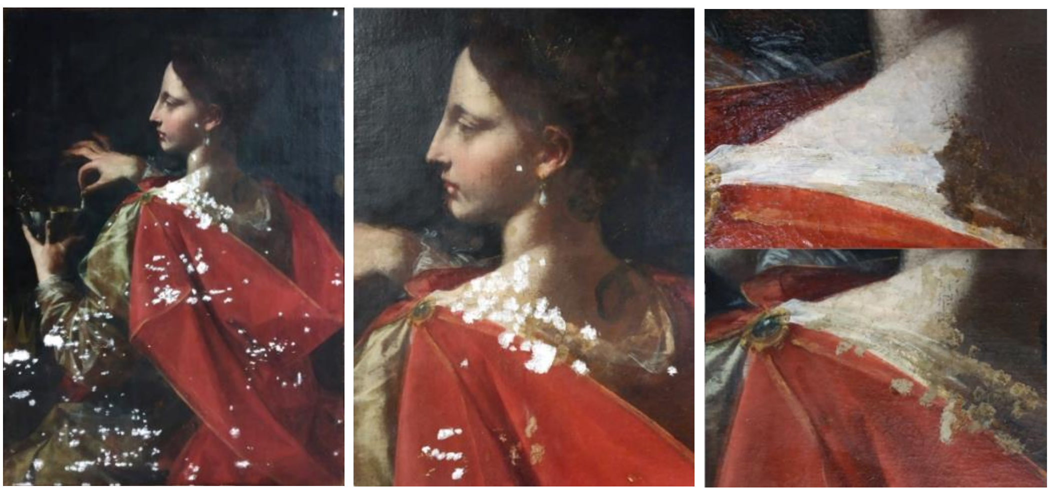
2. Case study

The methodology described above has been applied on a canvas depicting queen *Cleopatra*, attributed to Donato Creti (Fig 1). This artwork was presented to a private family by Pope Leo XII on 27 August 1827. The last restoring intervention executed on the artwork is from 2019, during which the restorers have discovered several pictorial remakes, some executed by the artist himself and others executed after his death by unknown artists or restorers. Donato Creti used to repaint the subjects; his contemporary painter an art historian Giampietro Zanotti says that -*"for his profession, he always studies, he sighs, he is anxious about the desire he has of perfection, and of glory, and he never tires of finishing and finishing his work"*[4]. The pictorial afterthoughts by Donato Creti, discovered during the restoration, concern the profile, the eye and the hands of Cleopatra (Fig.2). In addition, the painted canvas presents several interventions of ancient restorations such as grouting (gaps with stucco) and repainting especially apparent in the neck and shoulder (Fig.3).

Fig.1 - Cleopatra by Donato Creti (Cremona 1671, Bologna 1749), oil on canvas, 100×77 cm. Standard RGB; after the restoration was completed, image capture by Annamaria Amura.

(a) (b) (c)

Fig.2 - *Cleopatra* by Donato Creti; image captured during the restoration. (a) Removal of ancient varnish; (b)(c) Pictorial afterthoughts of the artist in profile and left hand.



(a) (b) (c)

Fig.3 - *Cleopatra* by Donato Creti, image captured during the restoration. (a), (b) Gaps covered by white stucco in 2019 and the original combing hair; (c) Old gaps from previous restorations and repaintings not performed by the original artist.

3. Methodology

The regions of interest (ROI) to be separated on the artwork surface can be classified into three categories: pictorial afterthoughts of the artist, previous restoration work, restoration work in 2019. The purpose of our methodology is to highlight and separate the different regions through image analysis. The input image dataset has been captured in different modalities: under visible light illumination, with two Nitraphot 500W diffuse-light projectors and a Macbeth Color Checker used as the reference, an RGB image was captured by a Nikon D800 camera. An infrared image (IR) at 1050 nm (Fig.1b), with a high dynamic range (16 bits), has been realized through a multispectral system based on Morovian G2-8300 (CCD KAF 8300 18.1 × 13.7 mm pixels 5,4 × 5,4 μm). The sensor is cooled to reduce the electronic noise during acquisition. The spectral resolution is obtained through interferential filters with ± 25 nm passbands around the central wavelengths 450, 500, 550, 600 and 650 nm in the visible range and 850, 950, 1050 nm in the near infrared.

Fig.4 *Cleopatra* by Donato Creti. A representative set of multispectral image capture by Vincenzo Palleschi

3.1. Image analysis through blind source separation

A painting can be seen as the combination of *M* different spectral components, namely the pigments or materials used to produce the colors. The hyperspectral data cube is thus a set of images where each channel shows the combination of the emissivities at a given wavelength, out of *N*, of all the different spectral components of the painting. The simplest model for such a combination is the linear, instantaneous one [5]:

$$x(t)=As(t),\ t=1,2...L \quad (1)$$

where *t* is a pixel index and *L* is the number of pixels in the input image, *x* is an *N*-vector representing the spectral samples captured at each pixel, *s*is an *M*-vector quantifying the presence of the different components at each pixel, and *A*is an NM mixing matrix whose coefficient ai,j represents the emissivity of component *j* at wavelength *i*. Ideally, in the scenario depicted by model (1), if we are able to extract vector *s* from the observed vector *x,* we would have estimated the *M* individual component maps. Since we assume that each of our regions of interest is characterized by an approximately homogeneous spectral appearance, that is, it includes a limited subset of all the components of the painting, the *M* estimated component maps could thus be inspected visually to locate the regions of interest.

Normally, we know neither *M*, namely, the total number of components in the image, nor *A*, namely, the emissivity spectra of all the components. The techniques used to estimate *s* are called of *blind* source separation (BSS [6]) since they solve the linear system (1) with no knowledge of matrix *A*. Of course, this missing knowledge must be replaced by some additional assumption. The Independent Component Analysis (ICA [5]) principle states that, if *A* is a tall, full-rank matrix and the single components are statistically independent and non-gaussian, a copy of vector *s* can be computed. Other approaches, such as Principal Component Analysis (PCA) and symmetric whitening [7, 8] can be shown in some cases to produce equally useful results, by assuming uncorrelation of the components. Thus, if the number of actual spectrally distinguishable regions in the image is not larger than *N* we can solve the BSS problem from (1) through an ICA technique. If the actual components are more than *N*, some of the ICA outputs will still contain mixtures of different components, thus possibly preventing us from recognizing our regions of interest. Especially when working with paintings showing many color components and restoration interventions, the latter is a very likely situation. In these cases, an often effective solution is to assume exactly *N* components, treat the data set by different strategies, and then inspect visually the output maps and select the ones that better highlight our regions of interest. Human judgement is inescapable in this situation. The final advantage is that the selected maps reproduce accurately the sought-after regions, thus helping an automatic procedure to extract them from the image domain.

In our case study, we assume the nine channels in Fig. 4 as our input data, and apply all the three processing strategies mentioned above assuming *N* components, thus obtaining 27 output images from which we try to locate three regions of interest, namely, the painter’s afterthoughts, the interventions by the ancient restorer and the 2019 restoration. Figure 5 reports the three output maps chosen, all resulting from the application of an ICA algorithm called FastICA [9], from which the three regions of interest can easily be segmented by any existing algorithm.

3.2. Self-organizing map segmentation

The Kohonen self-organizing map [10] is a particular kind of neural network based on competitive training algorithms [11]. The advantage of SOM when compared to other neural networks is the capability to preserve the topology of input samples [12]. Adjacent vectors in R^n are mapped to adjacent cells in the array, and adjacent cells in the array have similar position vectors in R^n [13]. SOM neural networks have long been used for the segmentation of different types of images due to their characteristics [14]. In this work, the SOM neural network has been applied to images obtained through a statistical preprocessing using Independent Component Analysis (ICA), Symmetric Whitening (SW) and Principal Component Analysis (PCA).

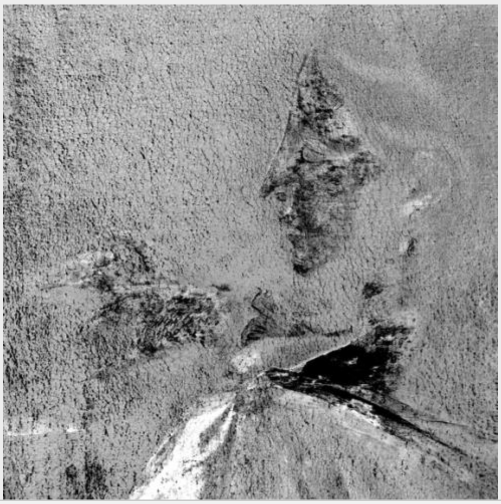
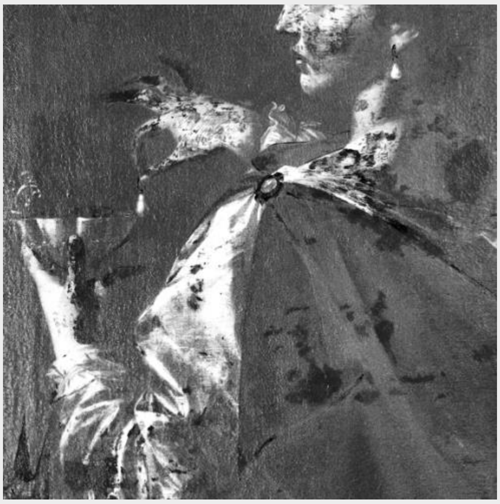
OUTPUT FASTICA	DETAIL	CATEGORIES
Channel 1 	**Channel 1** 	**Restoration work in 2019** This image segments in black the pictorial reintegration intervention performed by the restorer in 201 especially in the face and shoulder.
Channel 3 	**Channel 3** 	**Old restoration works** This image segments in black the old pictorial reintegration in particular visible on the profile of the forehead of the nose and neck, on the hand and in the red tunic. Moreover, the gaps are also put in evidence in black.
Channel 4 	**Channel 4** 	**Old restoration work and restoration work in 2019.** This image contains a lot of information regarding the different restoration interventions and the gray levels represent the thickness of the color used. Black represents a dense layer of color; gray represents a lighter layer of color.

Fig.5 Processed images chosen to identify the regions of interest. FastICA.

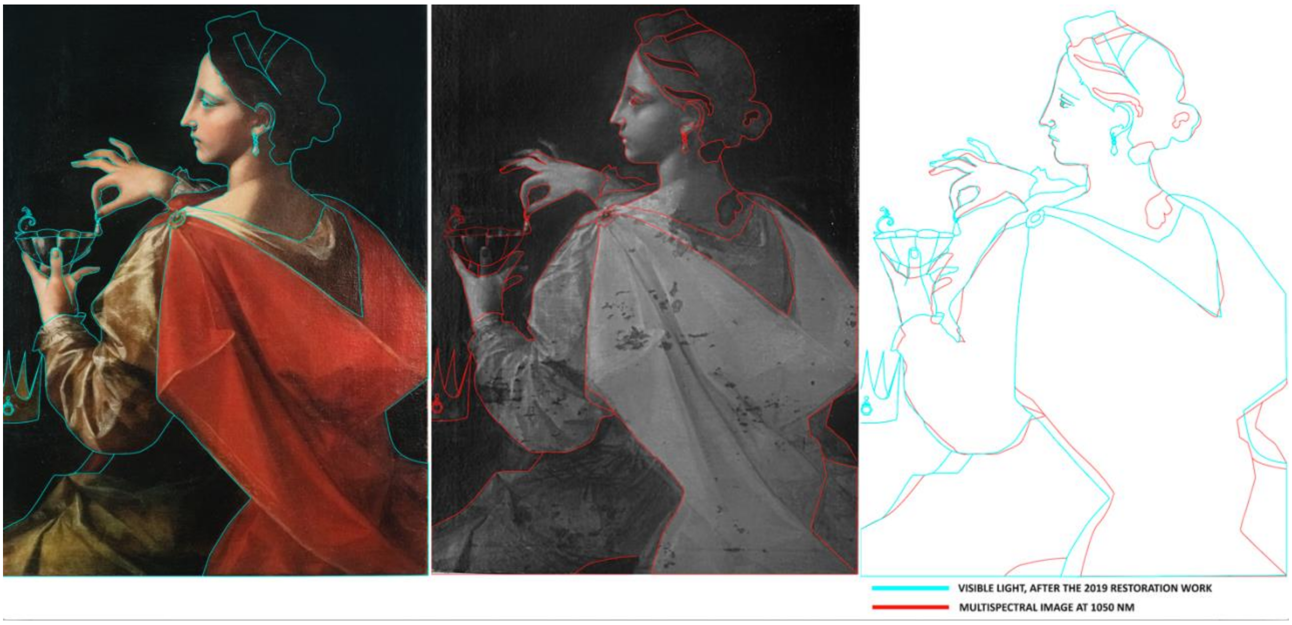
The intention is to test if we can obtain a sensible improvement in pattern recognition segmenting the ICA, SW and PCA results: taking the outputs of statistical treatments and using them as input from the SOM network, we should get as many outputs to which spatial coherence is returned. In the worst case we would have outputs equal to the inputs, in the best case we would have some outputs in which statistically segmented zones in different outputs are reassembled because pertinent to something that has the same optical behavior and topographical coherence. We had to carefully reconsider each of the output images to identify the ROIs. A useful secondary effect of the application of SOM is the binary masks obtained directly as outputs of the algorithm. These masks can be easily transformed into vectors.

INPUT FASTICA – OUTPUTS SOM		
Channel 1	**Channel 8**	
		These two binary masks classify the different restoration interventions and the different types of white pigment mixtures.

Fig.6 An example of binary mask images output of the SOM.

4. Results: features extraction, vectorization and final graphic documentation

After having visually analyzed all the outputs, the restorer interprets and transcribe the information into vector documents, called *Thematics Maps*, that are the main tool for communication and synthesis of the data collected, and are structured in systems including categories and subcategories. The *Thematic Maps* are formed by two graphically distinct models using different textures and colors and associated with a legend - 1. *Artwork Model* is the graphic representation of the shape of the artwork and its figurative symbology. 2. *Information Model* is the graphically describes the information regarding historical conservative data identified by spatially and dividing them into categories and classes [3]. It is worth observing that currently the graphic transcription of the data is performed manually by the restorer. The accuracy of each graphic relief is this different from any other. Moreover, the edges of the regions of interest are often very complex to be transcribed. Restorers often rely on architects for the architectural graphic relief or use commercial software without a standard methodology for other artworks. The extreme precision of this transcribed is a feature made possible by the automatic methodology we propose here. indeed, in our case, we have manually created only the design of the *Artwork Model* helping ourselves, when possible, with the raster to vector conversion of the SOM outputs, which in some cases delineated the edges of the figure with precision. Two *Artwork Models* have been created - the first represents the image in visual range RGB (Fig.7 a), the second is based on the multispectral image at 1050 nm (Fig.7 b). Through the overlap of these two drawings, it is possible to see the difference between the first version and the final version with the pictorial afterthoughts execute of the artist (Fig.7 c). Instead, the *Information Model* (Fig. 8) was created exclusively with semi-automatic procedures, with an automatic raster to vector conversion of the selected pixels of interest. Three outputs of FastICA (Channels 1, 3 and 4) were used to extract the edges and areas of the regions of interest. The extraction can be performed in two different modalities - through a *thresholding* process and through a process of selected the value of the pixel of interest (through *slicing* algorithm) [15], both present in many commercial tools. Each channel was processed individually through different threshold values obtaining various binary masks. The enhancement step is important here because the images output FastICA contain different regions of background that may cause confusion. To eliminate excessive noise and keep the edges clean, a *morphological filtering algorithm* has been applied to pixel selection [16]. Subsequently, have been created two vector documents through raster to vector conversion.



(a) (b) (c)

Fig.7- Two *Artwork Models* (a) image in visual range RGB, final version of the figure, (b) First version of the figure visible in multispectral image at 1050 nm. (c) Overlap of two drawings, difference between the first version and the final version with the pictorial afterthoughts execute of the artist.

(a) (b)

Fig. 8. Two vector documents-Thematic Maps obtained from the automatic extraction of the regions of interest from the ICA raster outputs. For each information a specific color is assigned.

5. Conclusion

The present work shows the first test to develop an integrated methodology that takes into account new technologies to support graphical documentation in the field of Cultural Heritage. Algorithms of image segmentation and neural networks have never been used in the field of graphic documentation, it is important to specify that the final result depends on the type of the opera and the quality of images used as input to these methods. Indeed, each opera has a different conservative history and it would therefore be impossible to construct a single procedural model that is the same for all. However, it is possible to create a guiding model and give specific indications on the quality of the images to be used, which for example must possibly be high resolution and free from noise and light reflections. The precision of raster to vector conversion depends on several factors, including the spatial resolution of the binary masks and the software used by the operator. Moreover, reading of the outputs of the algorithms must be carried out with great attention by the restorer, because sometimes in an image is combined different information. With this methodology, we have identified three distinct moments in the history of the opera in question and we have been able to map and document much more quickly and accurately than those of the current manual graphic documentation methodology. We are also studying to implement this methodology in open source software, in order to combine all operations into an easy to use toll for restorers.

5. Acknowledgements

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