Color segmentation and neural networks for automatic graphic relief of the state of conservation of artworks

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ABSTRACT

This paper proposes a semi-automated methodology based on a sequence of analysis processes performed on multispectral images of artworks and aimed at the extraction of vector maps regarding their state of conservation. The graphic relief of the artwork represents the main instrument of communication and synthesis of information and data acquired on cultural heritage during restoration. Despite the widespread use of informatics tools, currently, these operations are still extremely subjective and require high execution times and costs. In some cases, manual execution is particularly complicated and almost impossible to carry out. The methodology proposed here allows supervised, partial automation of these procedures avoids approximations and drastically reduces the work times, as it makes a vector drawing by extracting the areas directly from the raster images. We propose a procedure for color segmentation based on principal/independent component analysis (PCA/ICA) and SOM neural networks and, as a case study, present the results obtained on a set of multispectral reproductions of a painting on canvas.

KEYWORDS Multispectral images, Segmentation algorithms, Image analysis, Shape representation and analysis, Cultural heritage, Raster to vector, Neural networks

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1. Introduction

All the disciplines connected to restoration have always shown a deep need to achieve an extensive understanding of the object of interest, in order to develop a greater awareness of the actions needed and to perform them in the full respect of the object features. This knowledge can only be acquired through the study of the artwork's artistic and conservative history and the techniques and materials used for its realization. Several factors contribute to the realization of a restoration project, involving theory and methodology based on the relevant regulations (in Italy, issued by the Central Cataloging and Documentation Institute, iccd.beniculturali.it). Based on these regulations, all restoration interventions must be preceded and accompanied by documentation to create a sort of "medical record" of the artwork, within which all the collected data must be transcribed and archived in different forms and standard and geometrically correct modalities (The Venice Charter 1964) (Sacco 2002). At this cognitive stage, an important role is played by the transcription in graphics drawings of all the information obtained on the artwork. These graphics drawings, called *graphic relief* or *thematic maps*, are the primary tool for communication and synthesis of the collected data and are structured in categories and subcategories. The thematic maps are formed by two graphically distinct models using different textures and colors and associated with a legend: 1. *The artwork model* is the graphic representation of the shape of the artwork and its figurative symbology; 2. *The information model* is the graphical description of the information regarding conservative historical data (Sacco 2002). It is worth observing that currently, the graphic transcription of the data is performed manually by the restorer, and the multispectral images used for the localization of the information, are inspected only visually, or at most are optimized through a preprocessing by the experts (Dyer, J. et al. 2013). The level of detail of each graphic relief is different from any other, and the edges of the areas that contain the information of interest are often very complex to be transcribed. The restorers often rely on architects for the architectural graphic relief or use commercial software without a standard methodology. In 2003, the web-based information system SICaR was created for the georeferenced documentation within the network of the Italian restoration sites (sicar.beniculturali.it). Unfortunately, no image analysis tools are included in this software. This means that the graphic reliefs are performed by manually tracing the relevant areas with drawing tools, no image analysis strategy can be used to extract the relevant information, and no interaction is possible between the raster images and the vector graphics to help compile the thematic maps. In cultural heritage, the interest has focused recently on 3D modeling operations, image processing and artificial vision (Apollonio et al. 2017) (Tonazzini et al. 2019a, b) (Grifoni et al. 2019) (Vallet, J.M. et al. 2012) (Grilli, E. (2019). However, the authorities in charge of the conservation of cultural heritage (the Italian Ministry of Cultural Heritage, for example) still require graphic reliefs based on photographs. This motivates the quest we are pursuing for a standardizable methodology to separate and extract the relevant areas of interest from the raster images (photographs, *etc.*), then vectorize their boundaries and synthesize the results in the documents required by the authorities. A number of suitable image analysis methodologies must be selected that can solve, at least in part, the problems of reading and transcribing data. Besides avoiding results that are prone to personal biases, a partial automatization of this process can also reduce significantly the burden associated with the most time-consuming tasks. The method we are proposing here is based on our consolidated toolbox for the analysis of multispectral images. Spectrally discernable areas in the artwork image can be separated through statistical techniques such as principal component analysis or independent component analysis, and with the help of dedicated neural networks. With the essential contribution of the human expert, the areas relevant to the documentation are then recognized and segmented with the help of a dedicated image analysis process. The latter extracts semi-automatically the areas, separating them into different regions of interest (ROI), each corresponding to specific information attributable to the executive, restoration, and conservation history of the painting. The ROIs are then vectorized and used in graphic relief. This process is more objective and repeatable than any manual solution, and also enable the user better to perform geometric and statistical measurements on the resulting drawing.

2. Case study

The procedure described above has proved to be effective in different cases and with different restoration objectives. We demonstrate it here as applied to a canvas depicting queen Cleopatra, attributed to Donato Creti (Fig 1 a). This *opera* was donated to a private family by Pope Leo XII on 27 August 1827. Its last restoration intervention was executed in 2019 when the restorers discovered several pictorials *pentimenti* [1] executed by the author and several mimetic pictorials retouched executed after his death by unknown artists or restorers. Donato Creti used to repaint the subjects: his contemporary painter, the art historian Giampietro

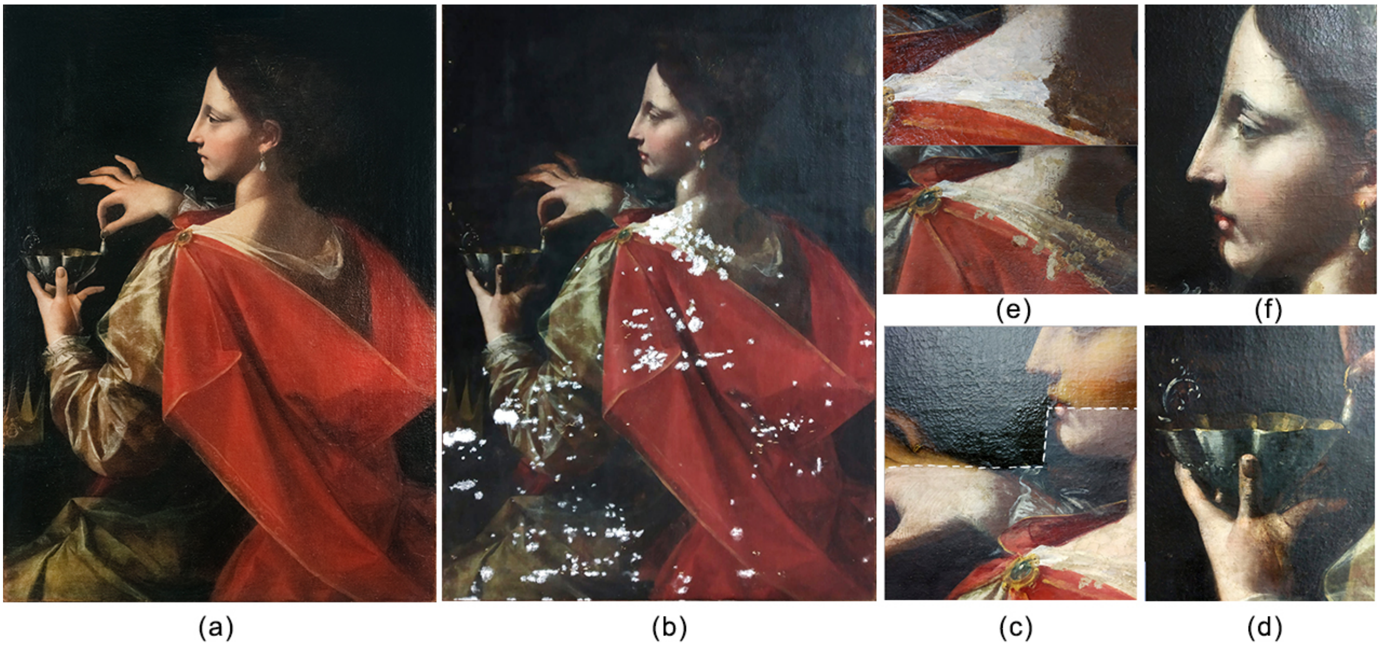

Fig 1 (a) Cleopatra by Donato Creti (Cremona 1671, Bologna 1749), oil on canvas, 100×77 cm. Standard RGB; after the restoration intervention, (b) image captured during the restoration. Gaps covered by white stucco in 2019; (c) Removal of old varnish; (e) Old gaps from previous restorations and retouches not performed by the original artist. (f) (d) Pictorial pentimenti make by the artist in profile and left hand.

Zanotti, says that – *"for his profession, he always studies, he sighs, he is anxious about the desire he has of perfection, and glory, and he never tires of finishing and finishing his work"* (Riccomi 2012). The *pentimenti* painted by Donato Creti concern the profile, the eye, and the hands of Cleopatra (Fig.1 f, d). Also, the canvas has several stuccoes (gaps filled with stucco, Fig.1 b), made in old restorations, and several mimetic retouches, especially evident in the neck area and on the shoulder (Fig.1 e).

3. Methodology

The ROIs to be separated can be classified into three categories: pentimenti of the artist, old restoration interventions, restoration interventions carried out in 2019. Our purpose is to highlight and separate the different regions through image analysis.

3.1. *Image dataset*

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.2b), with a high dynamic range (16 bits), has been acquired 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, and 1050 nm in the near-infrared. This choice ensures complete and continuous coverage of the visible range plus three infrared channels.

3.2. *Image analysis through blind source separation*

A painting can be seen as the combination of *M* different spectral components, namely, the colors of the pigments and other materials used to produce the original painting and the restoration interventions. These *M* spectral components represent the hyperspectral input data cube. Each of the *M* image channels shows a combination of the emissivities of the different materials at a given waveband. The simplest model to describe this combination is the linear, instantaneous one (Hyvärinen et al. 2001)

$$x(t) = As(t), t = 1,2,\dots,L \qquad (1)$$

where t is a pixel index, and L is the number of pixels in the input image, x is an *M*-vector representing the spectral samples captured at each pixel, s is an *N*-vector quantifying the presence of the different components at each pixel, and *A* is an *N*x*M* mixing matrix whose element a_{ij} represents the emissivity of component *j* at the *i-th band*. In this scenario, if we are able to extract vector s from the observed vector x, we can estimate the *N* individual component maps. Since we assume that each region of interest has an approximately uniform spectral appearance, the *N* estimated component maps could be inspected visually to locate the regions of interest. Usually, we know neither the total number *N* of components nor the emissivity spectra *A*. The techniques used to estimate s from x alone are called of *blind* source separation - BSS (Cardoso 1998) since they solve system (1) with no knowledge of matrix *A.* Some additional assumption must replace this missing knowledge. By the Independent Component Analysis (ICA) principle (Hyvärinen et al. 2001), if *A* is a tall, full-rank matrix and the components are independent and non-gaussian, a copy of vector s can be estimated from x . Other approaches, such as Principal Component Analysis (PCA) and symmetric whitening (SW, see Cichocki et al. 2002, Tonazzini et al. 2007), in some cases, produce equally useful results by simply assuming uncorrelation between the components. Thus, if the number *N* of spectrally discernable components in the images is not larger than *M*, we can solve the BSS problem by ICA or PCA. If the components are more than the image's channels (*M)*, some of the output channels will still contain mixtures of different components, possibly preventing the ROIs from being recognized. This is a very likely situation because each artwork presents many different components related to materials and techniques used in her conservative history, which are not always simple to separate spectrally.

For this reason, we often have different components mixed in the same output channel. In this situation, the only solution that has proved to be useful is the restorer's inescapable judgment. Indeed, it is always necessary to inspect the outputs channels to choose the ones that better highlight specific components in regions of interest (ROIs). Due to the impending judgment of the restorer, our methodology is defined as semi-automatic. The automatism is present in the segmentation of the *N* separated components, the extraction of the binary mask and the raster-to-vector conversion of the highlighted areas. The recognition and classification of the components are always up to the judgment of the restorer. In this case study of the methodology helped the restorer to locate the ROI and extract them from the image domain. We assume the nine channels in Fig. 2 as our input data and apply the three processing strategies mentioned above, each assuming 9 components, thus obtaining 27 output images, from which we try to locate the regions of interest related to the artist's *pentimenti*, to the old restoration, and to the 2019 restoration. Figure 3 reports the three output channels chosen, all resulting from the application of an ICA algorithm called FastICA (Hyvärinen et al. 2000), from which the three regions of interest can easily be recognized by the restorer and extracted by any existing thresholding algorithm.

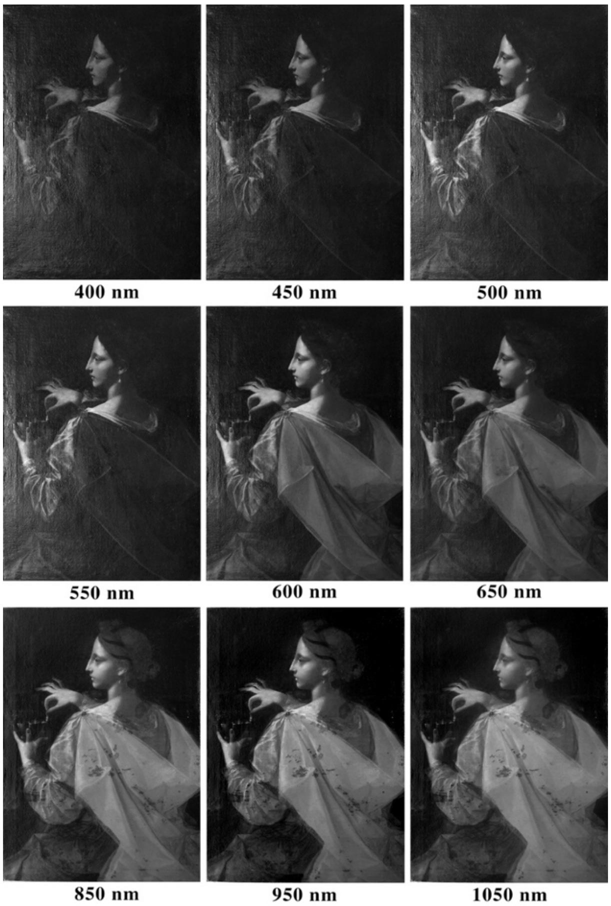

Fig.2 Cleopatra by Donato Creti. A representative set of multispectral image capture by Vincenzo Palleschi.

3.3. Self-organizing map segmentation

The Kohonen self-organizing map (SOM) is a particular kind of neural network based on competitive training algorithms (Kohonen 1998) (Rumelhart et al. 1985). Its advantage over other neural networks is the capability to preserve the topological properties of the input images (Uriarte et al. 2005) (Yeo 2005). SOMs have long been used to segment different types of images due to their characteristic of learning to respond in the same way to the same inputs (Kon et al. 1995). In this work, the SOM neural network has been applied, using as inputs the output images of the statistical preprocessing performed through ICA, PCA, and SW, with the intention of testing whether we can obtain a further improvement in ROI extraction. In the worst case, we can get output maps similar to the inputs; in the best case, we can get outputs in which different ROIs appear in different maps. The SOM outputs are binary maps, thus, besides improving the segmentation, they can also allow for a straightforward production of the contours of both the ROIs and the represented figures, without the need of applying any threshold. In figure 4, we show some examples of the results.

(a) (b) (c)

Fig.3 Some output channels of the FastICA algorithm from the multispectral set input. (a) Channel 1: here, the darkest regions correspond to the pictorial reintegration performed in 2019, especially in the face and shoulder. (b) Channel 3: the darkest regions in this ICA output correspond to the old pictorial reintegration. These regions are particularly visible on the profile of the forehead, nose and neck, the hand, and the red tunic. The numerous gaps also correspond to very dark pixels. (c) Channel 4: This output contains much information on the different restoration works; the gray levels represent the thickness of the color used. Black represents a dense color layer of color, whereas progressively light gray levels represent thinner color layers.

(a) (b) (c) (d)

Fig.4 Some SOM outputs with FastICA and PCA inputs. (a)(b) SOM output from FastICA: These two binary masks classify the different restoration interventions and the different types of a mixture of white pigments; (c) (d) SOM output from PCA: contours of the figure. This image was used to draw the Model of the Artwork in thematic maps.

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

After visually analyzed the outputs of all the elaborations, the restorer chooses those where the regions appear more clearly. In our case, we have manually drawn only the *Artwork Model*, helping ourselves, when possible, with the raster to vector conversion of the SOM outputs, which in some cases delineate the edges of the figure with high precision. Two *Artwork Models* have been created: the first, from the RGB image (Fig.3 a), it is the outline of the painting in its current state; the second, from the 1050 nm channel (Fig.3 b) and the Output SOM from PCA (Fig. 4 d), is the outline of the earliest version of the artwork. Overlapping these two drawings is possible to see the difference between the two versions and the artist's *pentimenti* (Fig.5 c). Instead, the *Information Model* (Fig. 4) was exclusively created with automatic procedures, starting from the three outputs of FastICA (channels 1, 3 and 4), with an automatic raster to vector conversion of the region of the areas identified, resulting into the extraction of edges and areas of the regions of interest ROIs. Each channel was processed individually through the different values of threshold, thus obtaining various binary masks. The extraction can be performed in two ways, both present in many commercial tools: by thresholding or by selecting the value of the pixel of interest through slicing algorithms (Mabrouk 2013). Each channel was processed individually through the different values of threshold, thus obtaining various binary masks. An enhancement step is essential here because the FastICA outputs contain backgrounds of different intensity, and this might confuse. A morphological filtering algorithm has been applied to the areas of FastICA to reduce noise and maintain linear edges (Zhao 2008). Subsequently, two vector drawings have been created through raster to vector conversion. All the operations used can be performed through different software tools. In our case, we used MatLab for image analysis (ICA, PCA, SW, SOM) and QGIS 3.6 for thresholding, raster to vector conversion, classification, and characterization of the ROIs, and to set the graphic relief (*thematic maps)*. It is essential to specify that the polygons extracted with this method can be read by other commercial tools widely used in the documentation for cultural heritage, such as AutoCAD and SICAR.

5. Conclusion

The present work describes the first steps towards the development of an integrated methodology that uses new digital technologies to support graphical documentation in Cultural Heritage. Algorithms of image segmentation and neural networks have never been used in this field, and our work demonstrates their potentiality in reducing subjectivity and speeding up the entire process. However, it is necessary to specify that the final result depends on the type of artwork and the quality of images used as input to these methods. In this respect, it is possible to create a guiding model and give

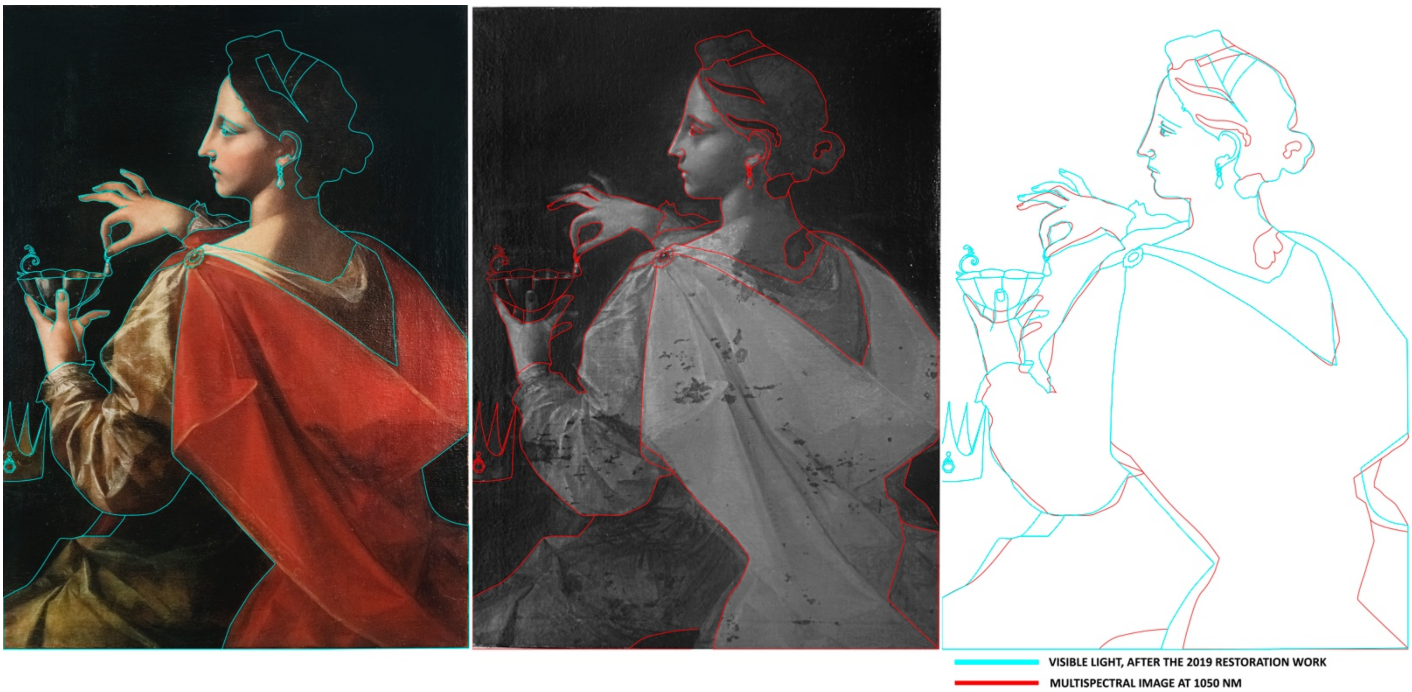

Fig.5 Two Artwork Models (a) image in visual range RGB, the final version of the figure, (b) First version of the figure visible in the multispectral image at 1050 nm. (c) Overlap of two Models, the difference between the first version and the final version with the pictorial pentimenti executed by the artist.

Fig.6 The two thematic maps obtained from the automatic extraction of the regions of interest from the raster outputs of the ICA are shown. For each information, a specific color has been assigned.

specific indications on the quality of the images to be used. For example, high resolution and limited noise and light reflections could be required. In this case study, the methodology has integrated and supported the planning process of restoration intervention, we have identified three distinct moments in the history of our case-study artwork and have been able to map and document the results much more quickly and accurately than any current manual graphic documentation. We are planning to implement this methodology in open-source GIS software to combine all operations into an easy tool for restorers. Moreover, implementing this methodology in a GIS system allows us to obtain a quantitative evaluation of the surface degradation, by applying the zonal statistical analysis tools to the polygons representing the ROIs.

6. Conflict of interest declaration

The authors declare that nothing affected their objectivity or independence and original work. Therefore, no conflict of interest exists.

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9. A short biography of the authors

Annamaria Amura is a Ph.D. Candidate in Computer Science at the University of Urbino. She holds a BS degree in Technology for the Conservation and Restoration of Cultural Heritage, Class 41, and an M.Sc. degree in Graphics of Images, LM12, Documentation, and Photography for Cultural Heritage. Her research interests include digital photography, image analysis, features extraction from diagnostic images, raster to vector automation method, GIS database, virtual restoration, and graphic documentation.

Anna Tonazzini is a senior researcher at the Institute of Information Science and Technologies, National Research Council of Italy, in Pisa. She coordinated several Projects in Image Processing and Analysis, Neural Networks and Learning, Computational Biology and Document Analysis, and is co-author of over 100 peer-reviewed papers. In particular, she was the ISTI responsible for the UE Project ISYREADET, and several national projects on historical manuscript virtual restoration and analysis.

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Notes

[1] *Pentimenti* is an Italian term that identifies the painting modification performed by the same author during the creation of the painting.

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