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Intelligent Image Processing and Optical Means for Archeological Artifacts Examination

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Abstract

This chapter describes how optical information and advanced image processing can be used to study archeological objects and artworks in order to determine more precisely and noninvasively the characteristics of the shape and color of artifacts. The purpose of this research is to develop a passive experimental technique for artifact investigation to help human experts make the best decisions in the process of authenticating and preserving-restoring objects. The method used is digital capture of object images followed by processing them with specialized software tools to analyze the chromatic characteristics and apparent geometric details. The proposed methodology consists of intelligently combining digital image analysis functions to build a set of chromatic-structural features useful for recognizing possible differences and estimating color and shape evolution. The investigation of the artifacts through digital image processing is a noninvasive and precise complementary method of analysis that can reduce the costs, and it must be extensively integrated into decision support systems for experts and curators in the field of artistic heritage preservation.

Keywords: digital image analysis, artifact authentication, conservation-restauration

1. Introduction

Conservation, restoration, and authentication of artifacts are activities performed by human experts using a multidisciplinary set of knowledge and corroborating information obtained through advanced investigation techniques. In general, human experts rely on their own skills of recognizing the composition of works of art using complex cognitive processes of interpretation of forms, colors, and textures in correlation with information about the technique of realization of the work being analyzed. Artifacts are important and valuable in their appearance, but this is affected by the passing of time, environmental physical parameters, as well as other natural or man-made causes. In current activities of authentication, conservation, and restoration, human experts are increasingly being helped by technical methods involving invasive and noninvasive analyses.

Optical information provides essential data about the appearance of objects and plays a major role in classifying them. The apparent representation of objects is perceived by the visual system through shape and color features. The shape of an object is determined by the spatial relationship between the points defining its

visible surface, while the color of each point is determined by the punctual interaction of the object with the optical radiation in the external environment. Between these two basic features of objects, there is a univocal relationship, meaning that the shape of objects can influence the perceived color, but not vice versa. The shape and color of objects can be assessed generally by geometric measurements or photometric techniques. Experimental methods are most effective in obtaining data to the extent that they do not affect the artifact. Optical scanning is a passive experimental technique, considered noninvasive, excepting the particular situations where artifacts may deteriorate due to exposure to light.

Based on the optical methods, quantitative and qualitative analyses can be made on the shape and chromaticity of artifacts of any kind such as distinct archeological pieces, stamps, paintings, and other forms of decorative art like mosaics, engravings, embroideries, and artistic upholstery. Image analysis models include special mathematical functions for calculating conventional measures to characterize shapes and parameters for color evaluation. Digital image processing is widely used in everyday life with many applications in the industry, health, transport, telecommunications, social security, and military. This chapter discusses the applicative features of digital image processing in the field of artistic and historical heritage protection by proposing complementary image-based analysis techniques for a better investigation of artifacts. The concepts discussed are supported by some applicative examples. The scientific purpose of this methodology is to obtain a relevant structural-chromatic set of features for an artifact at a certain time.

2. Fundamentals

2.1 The basics of colorimetry

Color is a perception of the surrounding world through our eyes. It is the most important graphic attribute of the images. Color is a notion that is defined from several perspectives as follows [1]:

- i. *Physically*: the color represents electromagnetic radiation in the optical (visible) spectrum between 375 and 760 nm, which are normally selective stimuli for retinal cones. The color of an object is given by the radiation components of the visible spectrum that are reflected by the surface of the object (the other components being absorbed).
- ii. *From a psychophysical point of view*: color is a characteristic of light that allows two fields of the same shape, size, and structure to be distinguished in the visible spectrum.
- iii. *From the psychosensory point of view*: regardless of the stimulus used, any light sensation is characterized by certain properties or chromatic factors: illuminance or brightness, chromaticity or hue, and saturation or purity.

Objects that make up an image can be achromatic (no color, i.e., invisible) or chromatic (colored). For example, the white light is achromatic, and white, black, and gray are neutral colors also considered achromatic. The chromatic colors are those that reflect the nonselective sunlight or artificial light, that is, it reflects equally all the lengths of electromagnetic waves visible to the human eye. In this category are the white, black, and all the hues between them (shades of gray).

These last mentioned colors are distinguished by one characteristic feature: brightness (illuminance).

2.1.1 Color properties

Color properties are defined in relation to human visual perceptual capacity and sensory psychic mechanisms. As components of light, colors have three basic features as follows.

- a. *Brightness or luminance*—represents the degree of intensity or amount of radiation energy reflected by a particular color. From the physical point of view, this property is determined by the amplitude of the light wave. Thus, bright colors reflect more light than dark ones. The brightest color is white, and the least bright is black. Generally, the colors at the edge of the visual spectrum (blue, purple) have a lower brightness than those at the center (yellow). A chromatic color is even brighter the farther away from the black.
- b. *Chromatic tonality* is the attribute that refers to the qualitative perceptual scale of a color. Physically, it is given by the predominant wavelength of the light that stimulates the visual analyzer. Thus, chromatic tone refers to the colors red, yellow, green, and blue, leading to their particular attributes like bluish-green, bluish-greenish, white-yellowish, etc., also called chromatic tones or hues. From a physiological point of view, the human normal eye discriminates between 2 and 5 nm of the wavelength of light radiation, thus being able to perceive numerous chromatic tones or color hues [2]. A classic experimental study reported since 1923 by Laurens and Hamilton quoted in [3] reveals a nonlinear distribution of wavelength discrimination between 0.25 nm and 7 nm across the visible spectrum range. According to [2], for instance, on the wavelength range of 760 nm (dark red) and 390 nm (violet), between 130 and 200 chromatic tones can be normally distinguished. These colors form color families arranged around the components of the chromatic spectrum, as follows: red has 57 distinct hues, orange 12, yellow 24, green 12, blue 29, and violet 16. In total, they make up to 150 perceptible shades; this number being also referenced by [4].
- c. *Saturation* is the purity or degree of blending of a color with white (total blending wavelengths in the visible spectrum), which gives the color to be more concentrated or pale (saturated). The color saturation is evaluated on a conventional scale of the distances at which a particular chromatic color is given relative to that achromatic white. From a physical point of view, saturation of colors depends on the uniformity of wavelengths perceived concurrently. A theoretically pure color is one determined by a single wavelength, the more we perceive more wavelengths while the color feeling is pale, less pure. If we perceive all the wavelengths concurrently, then we see the white. Due to the saturation property, the colors are classified as “strong” or “poor,” “heavy” or “light,” “bright” or “dead,” and “colorful” or “sad.” The saturation level affects the perceived chromatic hue. It is appreciated that by combining different degrees of saturation and roughly 200 chromatic tones, around 1700 chromatic hues can be obtained [2]. Based on physiological evidence and experimental psychology, the capabilities of the human visual analyzer to perceive the colors were estimated by different authors between 100,000 and 10 million distinctive colors [4]. These data tell us how performant should be a digital optical equipment to manipulate hues like humanlike.

2.1.2 Primary systems for color representation

Traditional color classification refers to how to obtain them. As is well known, colors are divided into the following categories:

- *Basic colors* (also called primary or fundamental colors) are those that by mixing them can be obtained all the other colors. These are red, yellow, and blue (RYB). The chromatic pattern to represent images on electronic systems is red, green, and blue (RGB).
- *Composite colors* are those that result from the mixture of base colors two by two. There are composed colors of degree I, colors composed of grade II (which results from the mixture of those of first degree, two by two), and so on.
- *Complementary colors* are those that mixed in appropriate proportions (which are found in the spectrum) give a neutral color (white or gray).

The above description, although conventional, is applicable to the artistic combination of colors, a technique well-known by painters for a long time. In practice, the emergence and development of photographic techniques and subsequently electronic means for processing and displaying images, the color manipulation process required the emergence of specific patterns for representing, capturing and transmitting image information. As chromatic perception is an expression of the reflection phenomenon of light, which is dependent on ambient illumination and the contribution of additional light sources, color representation patterns are found as formal color calculation tools.

The International Commission of Illumination (CIE), a body established in 1913, which through its division for Vision and Color coordinates the development of standards in modern colorimetry, by the recommendation of 1931 defined the so-called standard colorimetric observer proposing two systems primary equivalent color representation [5]. In principle, these are three-stimuli color spaces based on the Maxwell's trichromatic theory [6] in accordance with spectral sensitivities of the human eye.

The *first conventional system* proposed by CIE for color representation is RGB (Red Green Blue) in which color components are wavelength functions as follows: $R(\lambda)$ for $\lambda = 700 \text{ nm}$, $G(\lambda)$ for $\lambda = 546.1 \text{ nm}$, respectively, $B(\lambda)$ for $\lambda = 435.8 \text{ nm}$. The representation of the RGB color space with its combinations is shown in **Figure 1**.

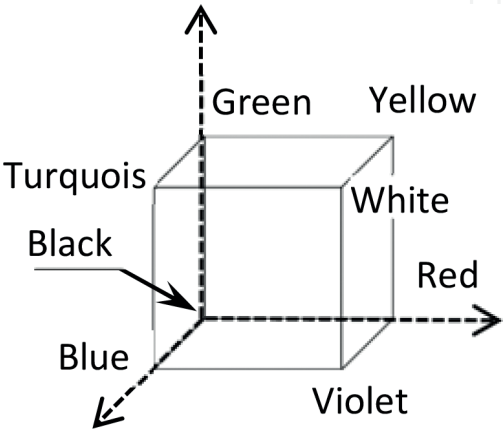


Figure 1.
Conventional representation of the primary RGB space and its chromatic derivatives.

The *second system* defined by CIE is XYZ whose functions are linear transformations of RGB system components expressed in a matrix form as follows [7]:

$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} 0.490 & 0.310 & 0.020 \\ 0.177 & 0.813 & 0.011 \\ 0 & 0.010 & 0.990 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \quad (1)$$

Derivative representation systems have emerged as a result of the diversification of the technical means of capturing and processing images that required the use of other rules for representing basic components. Thus, color television systems were imposed by NTSC and PAL standards by transforming the primary RGB space into three specific terms: luminance and two chrominance components. For example, for the PAL standard matrix transformation is as follows [7]:

$$\begin{pmatrix} Y \\ U \\ V \end{pmatrix} = \begin{pmatrix} 0.300 & 0.590 & 0.110 \\ -0.148 & -0.291 & 0.483 \\ 0.526 & -0.518 & 0.096 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \quad (2)$$

Another derivative color space was developed by Kodak under the name of PhotoYCC and consists in transforming the RGB reference space into the Luminance—Chroma—Chroma (YCC) components in three steps: a gamma correction, a linear transformation described in matrix, and a binary quantization on 8 bit. This system is used to store images on PhotoCDs.

Perceptual representation systems attempt to describe how human observers feel and express colors. Starting from empirical analyzes, it has been observed that people notice very well the properties of colors: brightness, hue and saturation. Perceptual representation systems attempt to approximate, through mathematical formulas, the psycho-physical effect of the three chromatic properties. Basic perceptual system HSV (Hue Saturation Luminance), also known in different versions as HVC (Hue, Value, Chroma), HSI (Hue, Saturation, Intensity) or HSL (Hue Saturation Luminance) is a more complex nonlinear transformation concretized by a rotation of the RGB chromatic space followed by a cylindrical or spherical coordinate transformation. There are several formulas for evaluating the three components of the HSV system proposed by different authors [8]. The generic representation of the HSV perceptual color space in cylindrical coordinates is shown in **Figure 2**. Conventionally, the numerical range for HSV components is the range [0, 1]. The hexagon has sides equal to 1 and is located at elevation $V = 1$. The conventional position of the white component is at the center of the hexagon, where

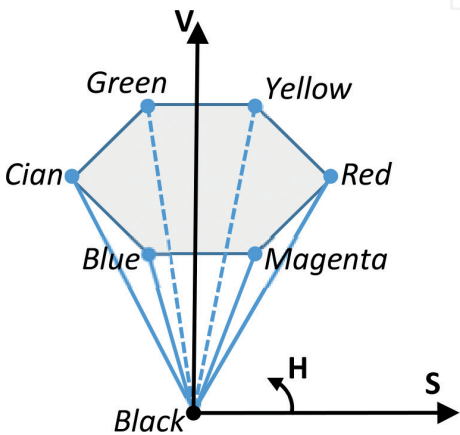


Figure 2.
HSV color space in cylindrical coordinates.

it is intersected by the Value axis. Thus, the white is not characterized by hue (it is “immune” to the variable H!); it has obvious saturation $S = 0$, and the value is maximum $V = 1$. The pure colors have the saturation equal to 1. The hue H is an angular coordinate on 360° and is conventionally represented on the $[0, 1]$ range, so that, each color of the hexagon peaks is at a distance of $1/6$ on the definition interval: Red $\rightarrow 0$, Yellow $\rightarrow 0.1666$, Green $\rightarrow 0.3333$, etc.

Alongside the CIE, the International Color Consortium (ICC) is a focus group that promotes new concepts and provides technical notes in the field of color standards and their representation with various techniques and electronic means [9].

2.2 About forms and their classification

2.2.1 Shape and geometry indicators

Shape is the outer appearance of an object that does not take into account its size. The shape of objects is perceived by their edges or contours. In a geometric sense, the shape of objects is described by properties that allow a classification of objects according to their appearance. Depending on their form and geometry, objects in nature can fit into a variety of hierarchically organized classes. The hierarchy of shapes is generated by the type of primitive graphics that describe the outline of objects, and their properties: their number and relative position, similarity or congruence so that by customizations or generalizations, very complex forms can be characterized. **Table 1** presents taxonomy of forms that can be used to characterize artifacts.

2.2.2 Measures of shape properties

Shape analysis is based on the detection and labeling of distinct regions on the artifact image. Based on these regions, the objects presented in that image evaluating certain properties commonly called shape measurements are estimated. Software utilities for image analysis provide a broad set of measures that can be used to characterize distinct objects once they have been detected in an image. For example, MATLAB programming environment contains powerful toolboxes for video analysis and image processing. Some of the measures used by MATLAB [10] are summarized in **Table 2**.

2.2.3 Shape recognition

Shape recognition is a decision process that is accomplished by a simple direct comparison action of a sample object with the reference object or by a more complex process of classifying template sets and subsequent reporting of unknown objects to these class sets. In the current work of examining artifacts, it is mostly to acknowledge direct comparison with the original. Here are the typical situations of authentication and restoration-reconditioning of artifacts in which knowledge of exact information about the original is essential.

When looking at artifacts with an unknown author is the question of framing the artwork at a certain time or in an artistic current, then recognition based on classification becomes important.

Comparison techniques include two methods of testing the match between the current object and the original: global matching and mathematical matching (based on significant properties). Global matching is applied based on artifact

Graphic primitive (base element)	Class	Subclass defined by the number of elements	Subclass defined by relative position of some elements (angles, for instance)	Subclass defined by the similarity of the elements (ref. to sides)
Line	Polygons (closed chain)	Triangle	Right triangle	Isosceles
				Any
			Equilateral	Equilateral
			Any	—
		Quadrilateral	Parallelogram	Square
				Rectangle
				Diamond
			Trapeze	Isosceles
			Right trapeze	—
		Pentagon	Convex	Regular/irregular
			Nonconvex	Regular/irregular
		Hexa/...octo/...decagon...	Convex	Regular/irregular
			Nonconvex	Regular/irregular
	Open chain	Connected segments	Opened ladders	Regular ladder
				Irregular ladder
			Zigzag shape	Regular
				Irregular
		Single segment	Horizontal/vertical/inclined	—
Curve	Closed curve	Circle/disc		
		Circular crown		
		Ellipse		
		Ovoid		
		Cardioids		
	Open curve	Circle arc		
		Ellipse arc		
		Parabolic arc		
		Hyperbolic arc		
		Spiral		
		Evolvent		
		Cubic		
		Sinusoid		
		Cycloid		
Combined	Circle sector		Semi-disc	
	Circular crown sector		Semi-crown	
	Ellipse sector			

Table 1.
Taxonomic hierarchy of 2D forms.

images by checking the superimposition of the composite in detail. Matching details involves image processing and extraction of properties that give the artifact uniqueness—called *minutiae*. The calculation of minutiae provides the measures

Property	Unit	Measure definition
“Area”	Pixel	Scalar representing the actual number of pixels in the region
“Centroid”	Pixel	Vector that specifies the center of mass of the region. The first element is the horizontal coordinate (or x-coordinate) of the center of mass, and the second element is the vertical coordinate (or y-coordinate)
“Eccentricity”	—	Scalar that specifies the eccentricity of the ellipse that has the same second moments as the region. The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. The value is between 0 and 1 (0 and 1 are degenerate cases; an ellipse whose eccentricity is 0 is actually a circle, while an ellipse whose eccentricity is 1 is a line segment)
“Orientation”	Degrees	Scalar representing the angle (in ranging from −90 to 90 degrees) between the x-axis and the major axis of the ellipse that has the same second moments as the region
“Perimeter”	Pixel	Scalar measuring the distance around the boundary of the region. It computes the perimeter by calculating the distance between each adjoining pair of pixels around the border of the region
“BoundingBox”	—	The smallest rectangle containing the region
“Extent”	—	Scalar that specifies the ratio of pixels in the region to pixels in the total bounding box. Computed as the area divided by the area of the bounding box
“ConvexHull”	Pixel	Matrix that specifies the smallest convex polygon that can contain the region. Each row of the matrix contains the x- and y-coordinates of one vertex of the polygon
“EquivDiameter”	Pixel	Scalar that specifies the diameter of a circle with the same area as the region. Computed as $\sqrt{4 \cdot \text{Area} / \pi}$
“MajorAxisLength”	Pixel	Scalar specifying the length of the major axis of the ellipse that has the same normalized second central moments as the region
“MinorAxisLength”	Pixel	Scalar: the length of the minor axis of the ellipse that has the same normalized second central moments as the region

Table 2.
Measure definitions of shape properties.

of the shape, and these must be known as a priority for the original. Usually, the comparison of artifacts is only at the level of minutiae with the establishment of decision strategies for validating or invalidating the match. The method for the minutiae-based recognition is devoted to biometric technologies, fingerprint recognition, face recognition, scar and tattoo recognition, etc., and is rigorously standardized [11].

Currently, the issue of automatic shape recognition has evolved in the field of artificial intelligence under the generic “machine learning” domain from statistical models toward the “deep learning” paradigm, proving spectacular performance especially in video analytics technology. These models are based on convolutional artificial neural networks that require massive pattern learning [12]. Their performance depends on the increased number of training patterns, while the uniqueness is the characteristic of the artifacts. An automatic pattern recognition system could be trained very easily to recognize a particular artwork of Monet among those of Cézanne, Renoir, or Degas, but he will not be able to learn to distinguish Monet de Monet or Monet from a fake Monet. Definitely, this remains the attribute of the human expert, assisted, of course, by advanced information processing tools.

3. Methods

3.1 Color software analysis

Automatic image processing tools are based on the interpretation of the pixel value that is designated by the primitive pixel graphics. The value of a pixel refers to its chromaticity and is measured by the so-called color index. An important problem is that the color index is a conventional measure that depends on the type of digital image: color, grayscale, or black-and-white. In general, real object images can be captured as color images in the RGB system and then converted to other image types by conversion or indexing. By indexing, color images require a lower amount of data due to the fact that the three RGB values are aggregated in one, but this involves numerical approximations. Thus, image indexing is done with the loss of original information about the value of the color components. Typically, grayscale and black-and-white conversions are used for image analysis, resulting in so-called binary images. These types of images can also be indexed, considering a gray-level reference threshold. For black-and-white images, there are two default indexing values: 0 and 1. Virtually, all digital image analysis methods apply to preliminary indexed images for which these methods have a degree of relativity and a conventional character. The morphological analysis of the objects, respectively, the forms and the composition of the shapes in a picture is also made on the basis of color, being affected by the weaknesses of this method. Investigating artifacts, however, requires a higher level of precision and the use of analytical tools to provide discriminators in accordance with human visual perceptiveness. We therefore show interest in an intelligent combination of using color-based digital image analysis techniques using both the RGB primary space and the HVS perceptual system.

3.2 Structural analysis

The issue of decomposing an image into component objects based on regions (the so-called region-based segmentation) is not trivial because of the ambiguity and relativity of the criteria. The principle of region detection is based on the application of a connectivity criterion for pixels of the indexed or binary image of the studied artifact. However, the method is dependent on the result of the decision about the pixel value, that is, the intensity (level) of gray at the point considered. Therefore, the result of the analysis depends on the enlightenment of the artifact. Some issues specific to the two methods are presented in **Table 3**. Thus, the standard methodology for analyzing forms that make up the artifact's image includes choosing the illumination pattern, setting thresholds for the pixel value selection range, and applying the connectivity criterion based on an adjacent rule of pixels having values in the same range.

Description	Method	
	Color analysis	Structural analysis
Principle	Independent	Based on chromatic differences to detect edges
Computing effort	Evaluation of the conventional pixel value	Uses more complex algorithms based on filtering spatial light distribution
Precision	Accurate numerical evaluations in color space	The result is generally affected by uncertainty

Table 3.
Comparative aspects of the methods used.

4. Artifacts study by intelligent image processing

4.1 Case study 1: tablet from Tartaria

Discovered in 1961 on an archeological site in the town of Tărtăria in Alba County, Romania, the objects known as the tablets from Tărtăria represent three ceramic pieces (made of loam).

The pieces, which were dated around 5300 BC by German researcher Harald Haarmann [13] have similar symbols to the Vinča culture, being the subject of numerous and controversial polemics among archeologists everywhere, since (in some opinion) the tablet is the oldest form of writing in the world. One of the tablets, the one of discoidal form, comprises four groups of signs, separated by lines. It is considered the closest to a true script with ancient symbols. Much of the signs contained in it are found in the letters contained in the Greek archaic inscriptions (but also in the Phoenician, Etruscan, Old Italian, Iberian writings). We have chosen for our study this engraved disc-shaped lenticular tablets with a diameter of 6 cm.

4.1.1 Preliminary analysis of chromatic components

It started from an RGB-captured image with the resolution 483×478 pixels under certain lighting conditions, available on the web [14]. The three-dimensional RGB data structure is accessible by reading the image with an application program and allowing it to be displayed as shown in **Figure 3**. Pixel values in terms of base chromatic components depend on lighting conditions so they include the effect of ambient light and any additional light sources. In this case, we are dealing with a three-dimensional object over which ambient light and especially additional sources produce significant effects on the image obtained. Therefore, we note first that color information is relative and uncertain as long as the exact pattern of illumination is unknown. Secondly, we notice effects on the perception of the real shape of the object and some shape details under the influence of the particular illumination pattern. Thus, uneven illumination, partial shading, glare as the effect of local dispersion on irregular surfaces, and the effect of roughness and texture add uncertainty to the perception of the object's appearance on the basis of optical means.

Under these conditions, the image analysis can be applied with the following features:

- i. Under controlled and uniform lighting conditions on stands specific to photometric measurements.
- ii. Using multiple images taken from different perspectives on the object.
- iii. Performing analysis on image portions with particular adjustment/selection of parameters for the investigated area.

A first quantitative analysis of the color composition in the image can be done with the instrument called the image *histogram* applied to the RGB base components. This is the distribution of the values of all the pixels in the image on each color component. For the studied artifact, the histogram of its image on the three components is shown in **Figure 4**.

It can be easily observed by evaluating dimensional graphs that red is the component with the highest weight, and blue with the smallest. This translates into the brightness (intensity) of the image in planes R, G, and B, as can be seen in **Figure 5**.



Figure 3.
First tablet from Tartaria. Picture (483 × 478 pixels).

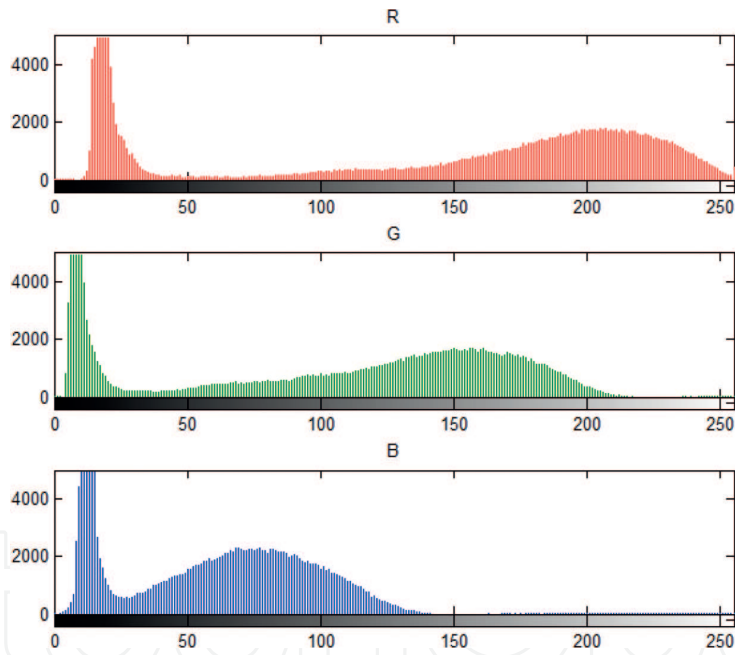


Figure 4.
Histogram of the image on the base components.



Figure 5.
Images separated on RGB base components.

Other qualitative information provided by histograms refer to their shape that tells us that the image does not contain pure green and blue components (value 255 is not reached), and their maximum concentrations are grouped at low (below 50), so with relatively low brightness.

Also, the red component is predominantly in relation to the other two at high brightness values (over 200), which confirms the chromatic aspect to the “hot” components of the object in **Figure 3**. It is obvious that in this statistic the pixels in the dark background, which do not belong to the object, also mattered. These can be largely eliminated through a level threshold filter and by matching the object within a suitable round frame. The histogram can be taken into consideration as an element in the formation of the structural-chromatic pattern of the artifact.

The second image analysis is done in the perceptual color space, which reveals the three essential characteristics specific to human visual analyzer: hue or color tones, color saturation or purity, and their brightness or illuminance. To begin with, convert the primary color image into the perceptual color space, for example, in the HSV system. The result of these transformations is shown in **Figure 6** by representing each of the hue, saturation, and value components in the corresponding images. The analysis is useful both qualitatively and quantitatively at the equivalent numerical data calculated by transforming $RGB \rightarrow HSV$ and interpreted in the coordinate system of **Figure 2**. To begin with, the image is poor in hues, supported by the uniformity of the numerical data of the hue parameter, which are massively grouped in the vicinity of the S-axis, so around the red component. Secondly, there is a saturation of gray-level typical components, the average calculated for the whole image being 0.5826 and a standard deviation of 0.014, which confirms insignificant information provided by saturation. Finally, the value illuminance component provides perceptually the most complete information, comparable to the red image plan (mean 0.5310 and standard deviation 0.0795).

We continue to focus the analysis on a distinct portion virtually cropped from the original image of the artifact, shown in **Figure 3**. The selected portion shows significant details of the artifact and is more uniform in lighting and chromaticity. The histograms in **Figure 7a** show a better concentration of RGB components around the maxima and the disappearance of the low luminance components compared to the histograms of the whole image of the artifact. The hue information H is insignificant, and in this case, the numerical values are very small (mean 0.0891) and the extremely small standard deviation (0.0208). Saturation is slightly higher than the whole image with an average of 0.6311, but the standard deviation is only 0.0103; thus, there is enough information uncertainty, which can also be seen from the S-plane image of **Figure 7b**. Finally, the perceptual luminance component with a higher average than the previous one of 0.6912 and the standard deviation 0.0415 provides the correct information, similar to the chromatic components red and green.

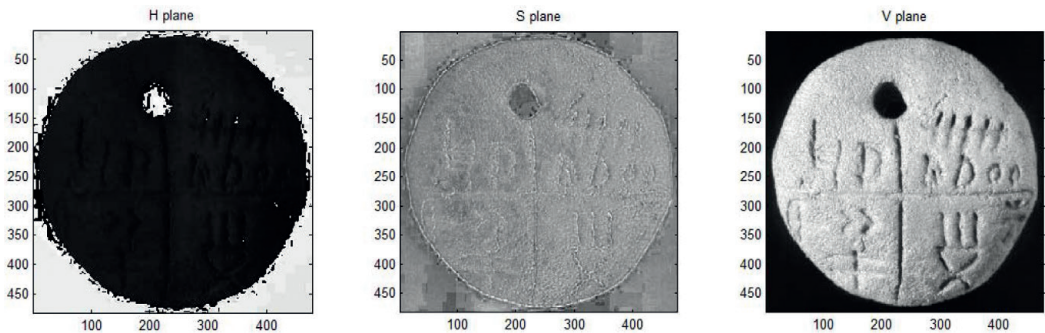


Figure 6.
Image components in the hue-saturation-value perceptual system.

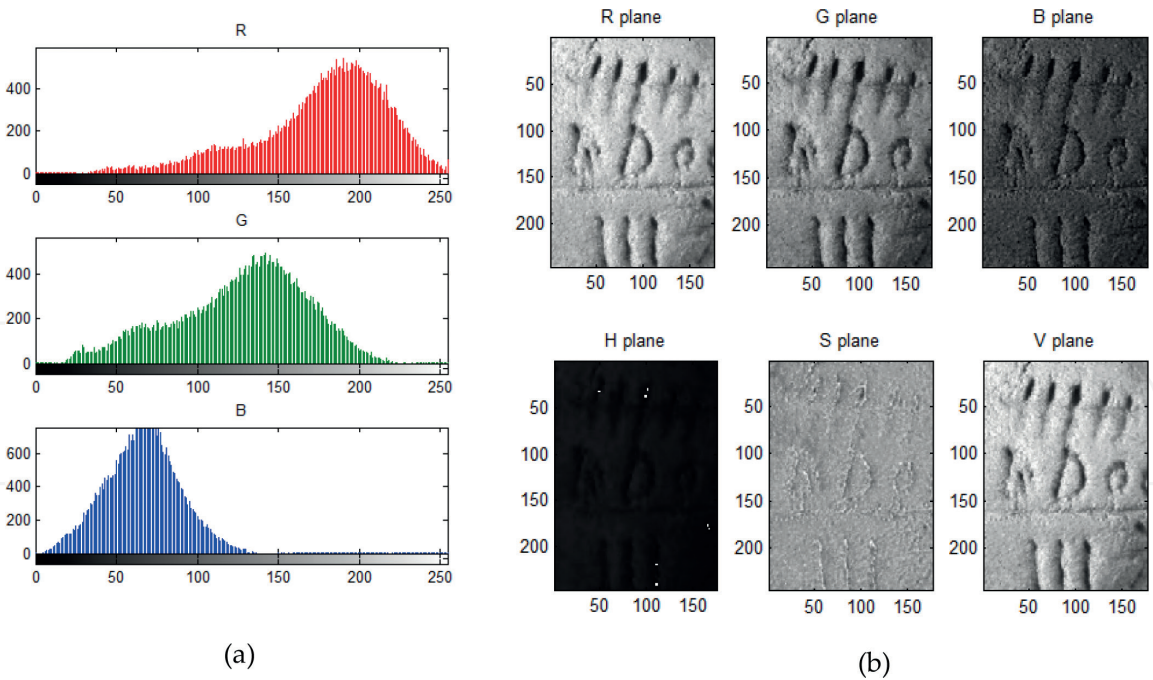


Figure 7.
Color analysis of a detail.

4.1.2 Shape analysis

For three-dimensional artifacts, estimating forms is a complex problem characterized in most cases by uncertainty. The uncertainty comes mainly from two sources: (i) data accuracy, which in the case of images is affected by nonhomogeneous illumination, respectively and (ii) the lack of specific processing models and algorithms. In practice of authentication and especially restoration preservation, the physical presence of objects is indispensable. However, in the stage of elaboration of the structural-chromatic pattern of artifacts, the extraction of some form characteristics and their quantification may be reliable provided that image acquisition is made in optimal and reproducible conditions.

In the following we will show how to evaluate some shape property measurements for already studied tablet from Tărtăria.

The method involves three steps, which are described as follows:

- a. Preliminary processing in the color space by following the next steps:
 - The original image is converted to grayscale.
 - The image obtained is filtered, for example, by applying, for instance, median filter of order 2.
 - The new image converts to binary (black-and-white image) based on a threshold of intensity.
- b. An algorithm is used to identify pixel regions that enjoy the same property by following the following steps:
 - Check the connectivity of the pixels with the neighbors in variant “4-connect” or “8-connect.”
 - Label the linked regions as the list of component objects of the image.

- c. Calculate the different properties of the component objects in the image:
- Additional filters for object selection apply, for example, regions detected on artifact that have a larger area than a required threshold.
 - A list of shape property measurements is made.

Thus, for our artifact, after the application of steps (a) and (b), a number of 107 component objects resulted in the binary image of **Figure 8**. These objects were detected as image regions above the conversion intensity threshold, and so all the pixels belonging to them were changed to 1 (white). Therefore, the image is analyzed for brighter areas. In step (c), it was decided to select the objects by filtering according to the $\text{Area_object} > 200$ criterion, and so only five regions corresponding to objects highlighted and numbered in the order of their extraction by the algorithm were retained. These objects are marked in **Figure 8** by their centers of weight designated (see red points) and labels. The list of calculated properties of the five components considered is presented in **Table 4**.

For the analysis of the engraved symbols on the artifact, the darker areas will be those of interest. Therefore, it is necessary to perform a reversal of the binary image by the complementary operation so that the regions of interest (the darker depth) pass into 1 (white) and can be evaluated as in the previous situation. **Figure 9** shows the result of complementing the initial image and marking the detected forms with the position of the calculated center of weight. In the middle image, all regions detected are marked (with blue dot), most of which belongs to light scattering small areas. In the picture on the right, the number of interest regions was dramatically reduced by applying the area filter ($\text{Area_object} > 200$). Most of the parasitic areas were removed, and the remaining ones belong to the symbols of interest and were marked in the red points. It is true that based on the image available for processing, not all of the symbols have been detected. It can easily be noticed that due to uneven illumination, the shaded area on the lower-left side of the image requires separate treatment.

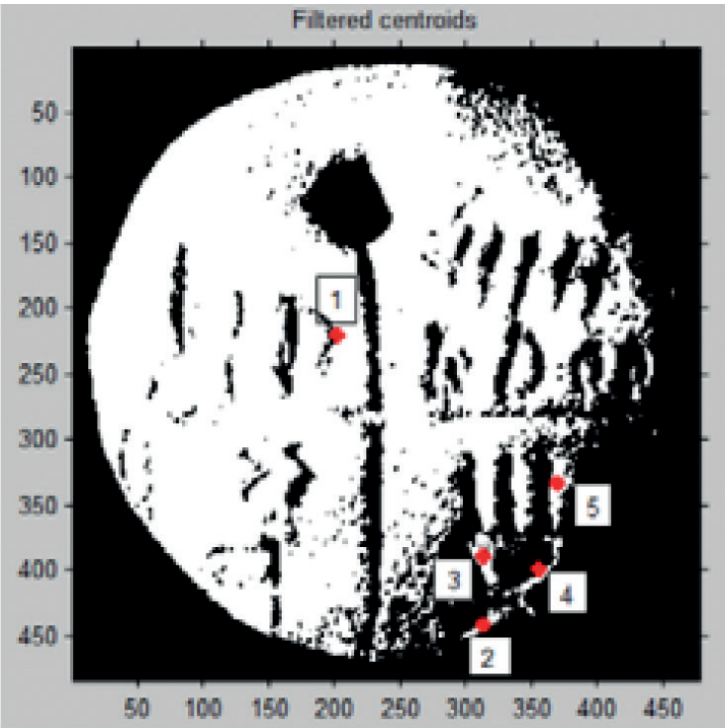


Figure 8.
Image of the position of selected objects.

Region no.	Area	Perimeter	Orientation	Eccentricity	Center of weight	
					Xc	Yc
1	111,222	4065.5	57.88	0.5486	201.64	220.55
2	222	100.6	36.87	0.9665	312.93	441.57
3	427	115.6	−74.43	0.9270	313.74	390.27
4	313	187.2	55.68	0.9769	356.02	400.18
5	611	206.4	85.96	0.9641	370.17	332.94

Table 4.
Numerical shape properties.

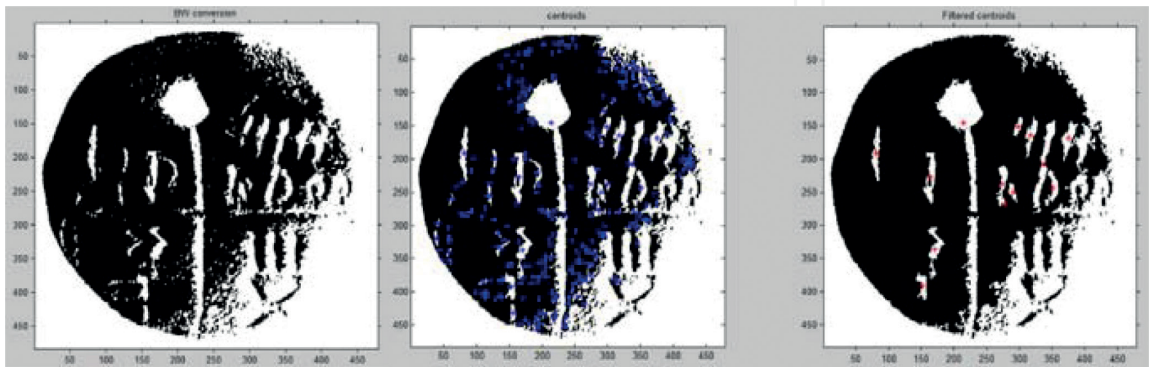


Figure 9.
Detecting the engraved forms on the complementary image.

Data obtained through shape analysis complements the information on the structure of the artifact. They can serve as a basis for comparison in the process of authenticating artifacts or evaluating their alteration (degradation) over time. The usefulness of these data depends on the uniformity of image acquisition conditions, the most sensitive factor being illumination.

4.2 Case study 2: C. Monet’s paint “Water Lilies and Japanese Bridge”

Famous painted works of art are most commonly reproduced for commercial purposes. Combating illicit activities with paintings implies the development of the most effective methods for examining them for the purposes of authenticating them and detecting counterfeits. The restoration in terms of rehabilitation of the paintings, in the sense of intervention on the painting itself, does not apply to the easel works than in some exceptional cases in accordance with national legislation and the European convention for cultural heritage protection. Reconditioning and even reproduction (restoration) are fully practiced in the case of monumental paintings, most often in the case of frescoes. In both categories of problems, knowing the original is essential for obtaining the necessary reference data in the authentication process or reproduction for restoration purposes. To exemplify the proposed methods, we chose from the easel painting category the Claude Monet’s work from 1897 to 1899 entitled “Water Lilies and Japanese Bridge.” The original painting is oil on canvas with the dimensions of 89.7 × 90.5 cm and is exhibited at the Princeton University Art Museum at the Department of Modern and Contemporary Art. To apply the method, we chose the original jpeg file with the 1031 × 1001 pixel resolution shown in **Figure 10** [15]. The preliminary analysis reveals from the chromatic histograms (see **Figure 11**) that the predominant luminosity is green, but as a

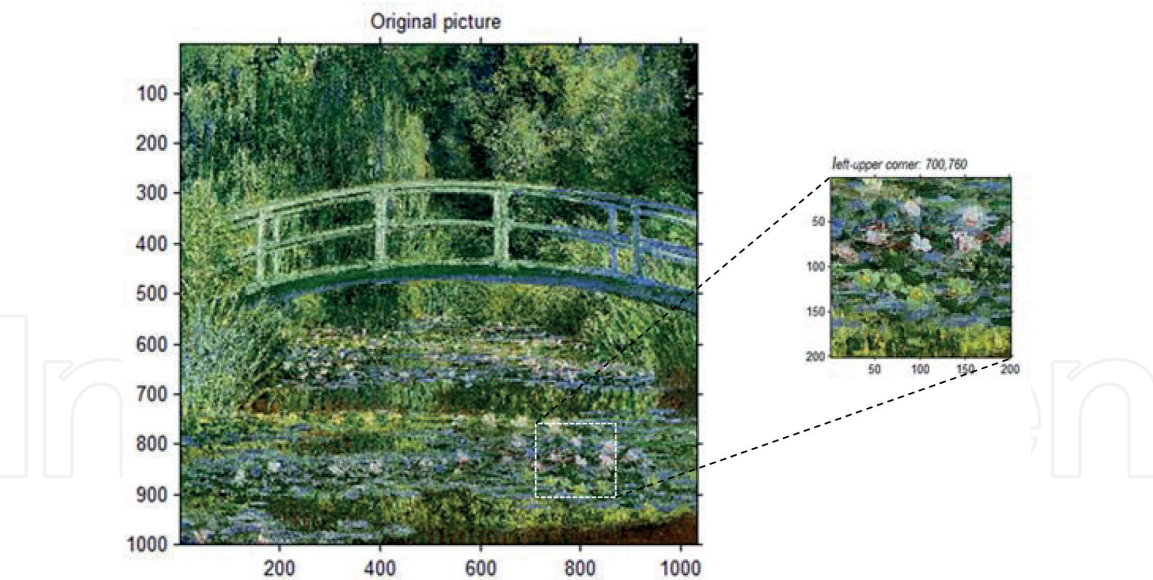


Figure 10.
Original painting of “Water Lilies and Japanese Bridge” (C. Monet) and detail.

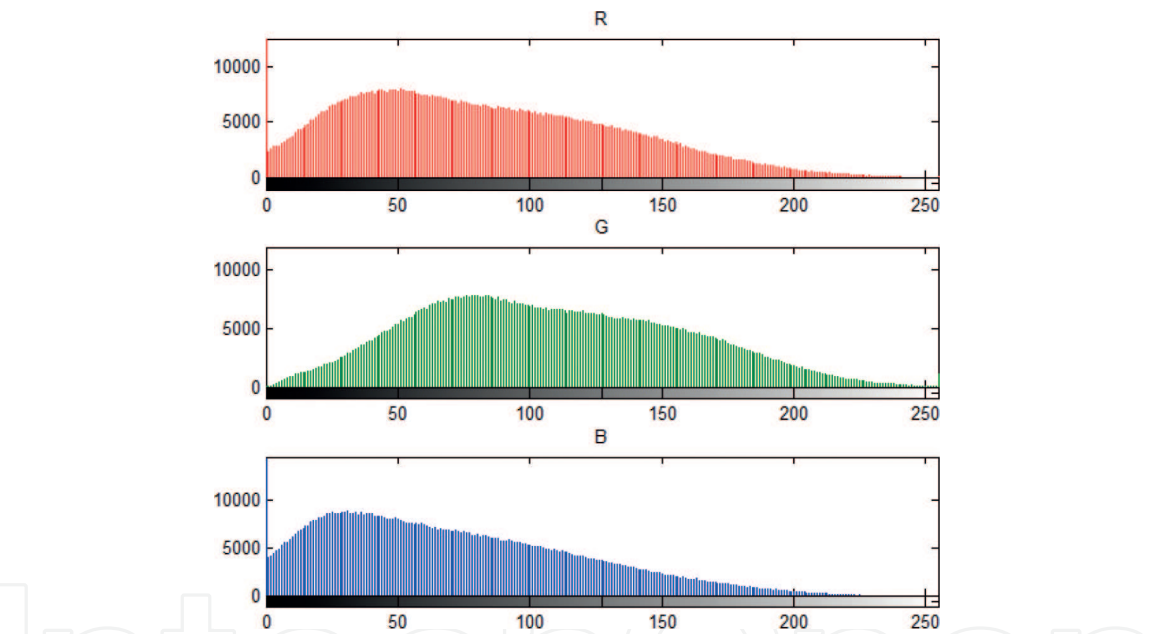


Figure 11.
RGB histograms.

whole, the three components have luminosity below half the conventional scale 0–255. Histograms show that its peak values are reached for the minimum brightness at which more than 10,000 pixels contribute with at least one of the red or blue components equal to 0, corresponding to the dark portions of the painting.

The information given by the analysis of the image planes R, G, and B shown in **Figure 12a** reveals a relatively balanced brightness of the three base components. Going forward with the analysis in the perceptual color space, we find the existence of good visual information in the hue plane, which is supported by the numerical distribution of the hue index on the whole field 0–1, with the greatest weight between 0.1 and 0.7 covering virtually all the chromatic derivatives. This is a confirmation for impressionist painting and C. Monet’s particular style of creating iconic tones. In this painting, the artist used mostly green tones and tones to yellow but also tones between turquoise and blue. This results from the construction of the hue histogram shown in **Figure 13a**.

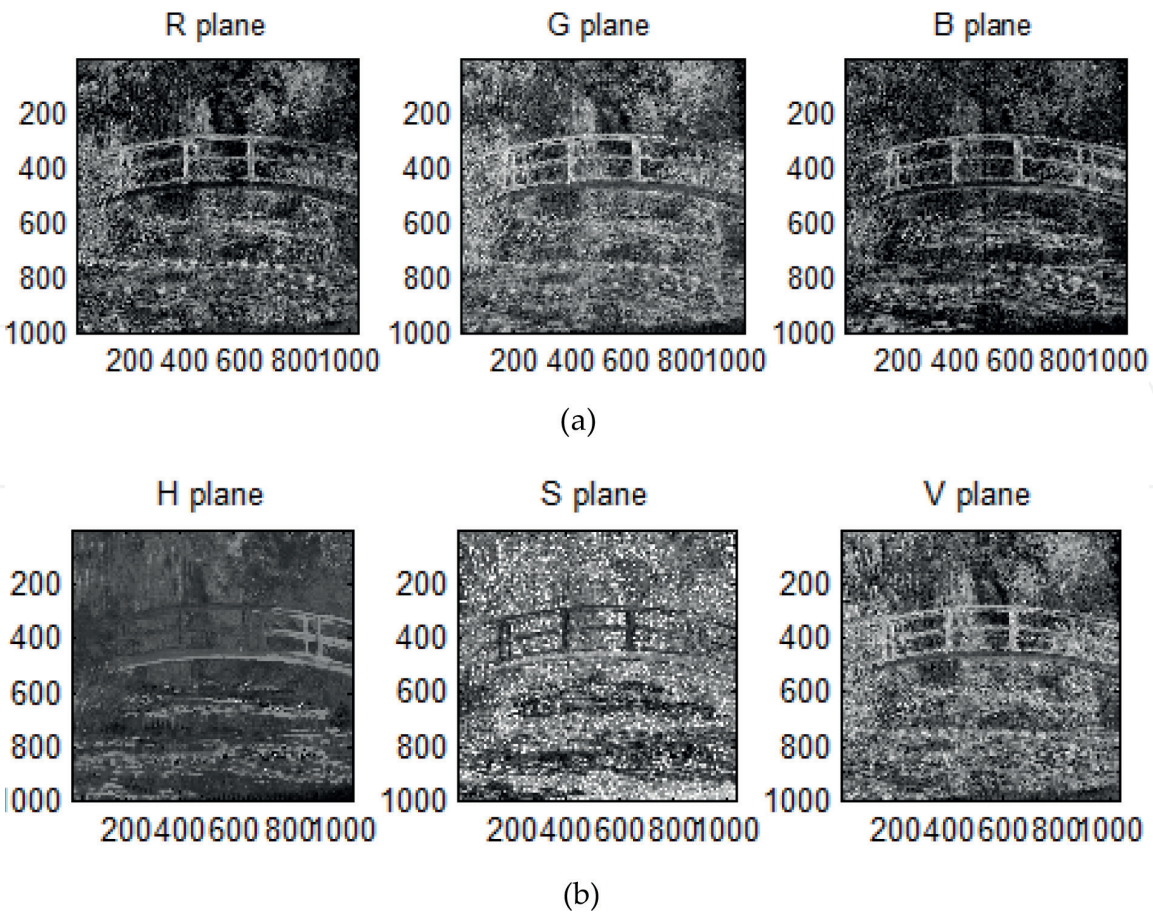


Figure 12.
“Water Lilies and Japanese Bridge” in (a) RGB color system and (b) HSV perceptual color system.

The saturation analysis shows an average of 0.49 and a regular distribution of saturation index at the level of the whole image, close to the Gaussian form, as can be seen in **Figure 13b**. Two particularities in the histogram of saturation are worth highlighting. The first refers to a significantly larger number of pixels (exactly 11,151) that define saturation peak very close to the median level of 0.5 (peak 1), which corresponds to the mixed half-half white colors. The second feature refers to a peak equal to 1 (peak 2), which corresponds to pure colors. From the saturation matrix evaluation, a number of 56,569 pixels corresponding to pure colors resulted. It can be said that Monet used in addition to the multitude of specific nuances and pure colors and mixtures of them with white half-half preparations. With respect to the whole picture, it is estimated that the proportion of the use of the mentioned colors is 1 and 5.48%, respectively, and the remaining 93.52% are blends made by the artist. Analysis of the perceptual value parameter reveals a global overall brightness at the level of the whole array. The value index distribution shown in the histogram of **Figure 13c** reveals an acceptable uniformity with a maximum around 0.3 with a similar shape of the green component distribution. There was no pure black in the image and barely pure white—1333 pixels (about 0.3% of the total)—detected. It can be assumed that the artist avoided the use of these chromatic components in this work, or if he has used them to some extent, they have altered in time.

4.2.1 Analyze an image detail

The selected detail is a cropped image portion with a square frame from the pixel 700,760 to 900,960 as shown in **Figure 10**. We summarize the analysis of the histograms obtained in the HSV perceptual color system, as they are represented and annotated in **Figure 14**. Regarding the hues, we can see the following:

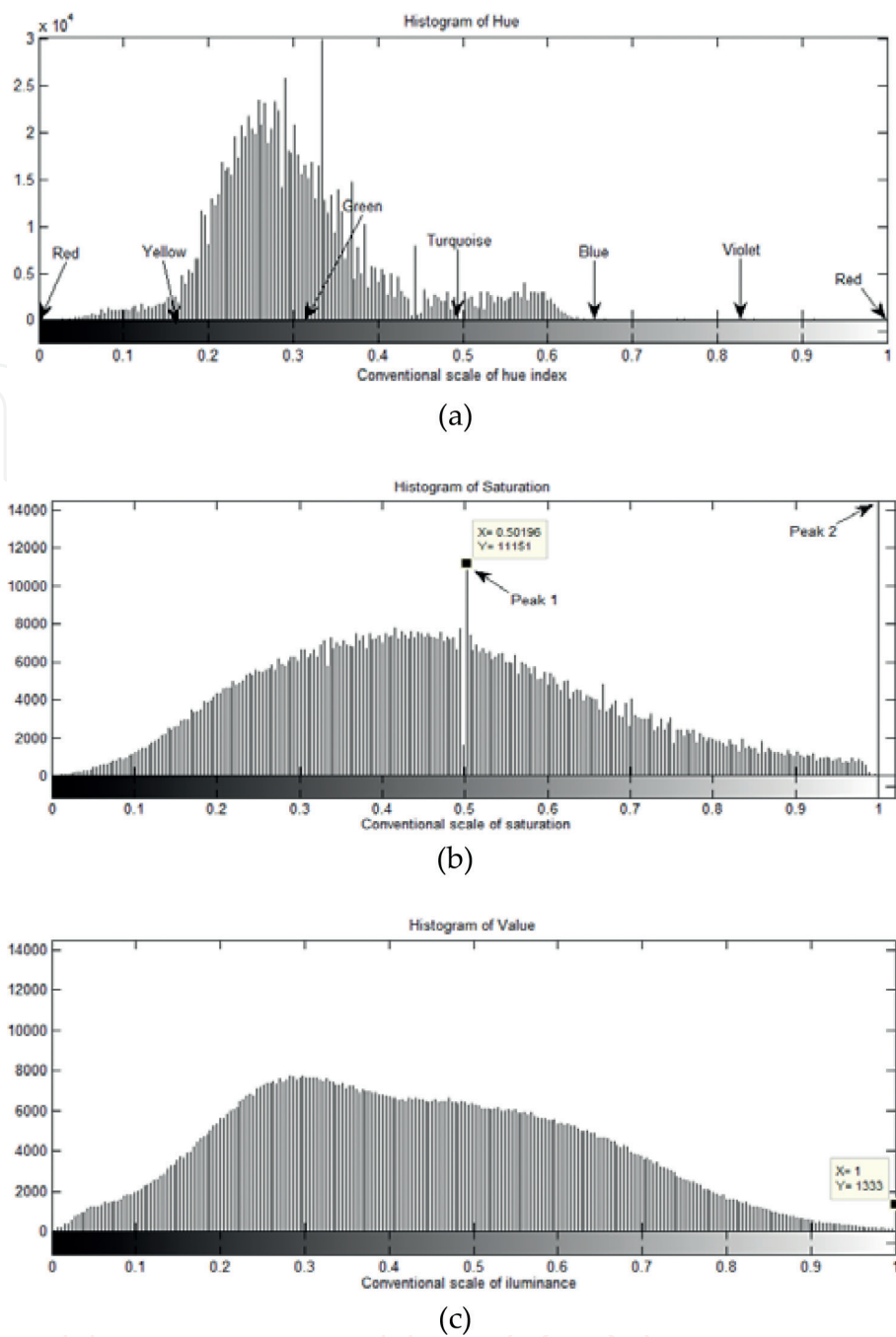


Figure 13.
Histograms of perceptual components HSV.

- They are massively distributed in the yellow-green and turquoise-blue portion of the color space.
- The distribution is uneven, showing numerous spiky peaks.
- The distribution on the analyzed detail retains the aspect and proportion with the distribution for the whole image.

The findings lead to the following conclusions:

- Confirm the observer/human expert’s visual perception of the range of predominant hues.
- Irregularly distributed peaks highlight the specific touches by which the artist applied the respective hues.

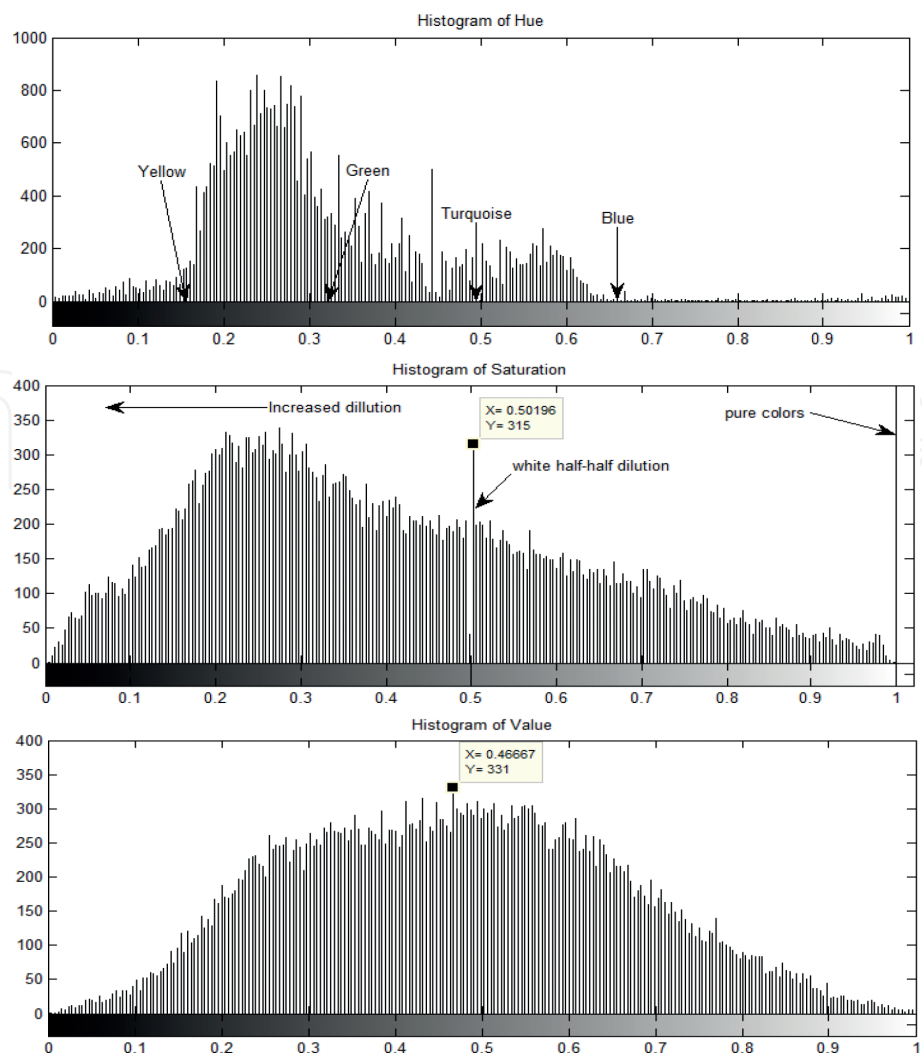


Figure 14.
Histograms of detail in HSV space.

- The weight of the hues is relatively uniform throughout the composition, which is in line with the representative impressionist note of this painting.

Saturation analysis at the level of detail reveals the following two interesting aspects:

- The weight of the saturation indices is shifted in the range of 0.15–0.40 from the whole image 0.25–0.60, the average of the values decreasing accordingly to 0.4254 from 0.4913.
- Histogram of detail reveals the same two distinct components present in the full image.

The conclusions lead to the following assumptions:

- The artist used in this area the painting colors with a slightly larger white dilution. The representation of the water lilies has certainly imposed this.
- The artist used both pure and half-diluted colors as well as the entire composition. These two components present in both histograms of saturation can be a way of recognizing the work.

The histogram of illumination reveals the following:

- A slight increase in the average value from 0.4327 to 0.4718. The maximum value is at the illumination value of 0.4666, while for the entire image, it is about 0.3000. Therefore, the detail area has brightness above the average of the whole picture.
- The distribution is more uniform and with a high degree of symmetry around the mean, approximating to a large extent the Gaussian curve.

4.2.2 Structural analysis of the detail

The detail area of painting, as shown in **Figure 10**, was selected in order to exemplify a local specific structural analysis. Detailed structural analysis of detail can provide essential information for evaluators and restorers. The chosen detail in this case is relevant because it contains a variety of colors and irregular shapes in relation to the whole image. Determining a structural pattern for the studied picture detail is done by analyzing the forms by passing the methodological steps enunciated in the first case study. By applying the image processing tools and the evaluation of the forms, the elements necessary for calculating the shape indicators are successively obtained.

Figure 15 shows successively the result of image conversion in black-and-white, extracting regions with a filter for the area of detected regions and determining the center of gravity of the objects thus filtered (see red dot markings on the right). It is noted that the algorithm used light information to convert the image to black-and-white using an index value (intensity) threshold. The middle image in **Figure 15** shows the conversion result with the threshold automatically calculated by the algorithm based on average light. The white parts of the image correspond to pixels whose intensity exceeded the required threshold, so a considerable number of regions were detected.

At this stage, we could decide either to raise the intensity threshold to reduce the number of regions by keeping the brightest or to apply an extra filter to one of the shape measures, for example, the area. Applying the second option to $\text{Area_object} > 200$ has led to considerable reduction of regions and retaining more significant shapes, which are actually the largest and brightest pixel regions connected (see **Figure 15**, right-side picture).

Nondestructive methods of this type are effective in internationally recognized restoration and conservation analysis. We have chosen to apply them to art and archeology components that are part of the cultural heritage of Romania, are in a degree of advanced deterioration, and are threatened with extinction and for which any other method would not be efficient, in the field of fingerprint, authentication. For a more complete overview on the discussed methods, we extended the analysis with other two examples including metopes from Roman metopes to Tropaeum

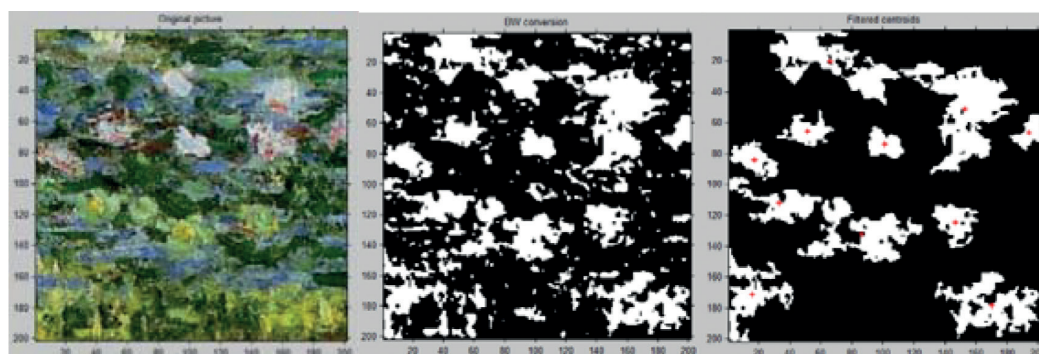


Figure 15.
Successive steps in region detection.

Traiani Monuments, Adamclisi, Dobrudja, and frescoes from Loggia Mathia to Corvin Castle, Hunedoara, Transylvania.

4.3 The analysis of Roman metopes to Tropaeum Traiani Monuments

A number of three metopes were compared based on the high-definition photos taken at the original artifacts. The chosen metopes are unpainted stone bas-reliefs as shown in **Figure 16**.

Chromatic analysis shows a well-balanced distribution of the RGB components for all three artifacts, which is in line with the nature of the base material—stone (most likely granite). The slight differences are done by the influence of dark areas in the pictures and the frame around the actual artifacts that are most present at Metopes 1 and 2. The RGB pattern of Metop 3 is the closest to the middle of the range, that is, gray. Perceptual color space reveals the nonspecific hue (H) distributions: singular (isolated) tones can be seen on the whole spectrum, but the remarkable concentration is still in the range of “warm” colors. The saturation (S) is definitely low: there are no pure colors in any cases. The luminance (V) is good in all three cases making them visible and comprehensible to the human observer. The discussed results are based on the histograms depicted in **Figure 17**.

Shape analysis aims to detect the significant regions of the artifacts in order to record them as a structural pattern. The basic steps for image processing described in Section 4 are followed. To obtain a better detection of the main contours of these bas-reliefs, we use the complements of the black-and-white images displaying darker and shaded areas in white. In **Figures 18–20**, the results of image processing for all three metopes are represented. In this analysis, we used classic color-based segmentation and a useful tool to label the detected regions with colors. The colors are conventionally allocated to the regions of connected pixels having the same level of darkness. In this way, the visual analysis of the shape itself can be made easier, and the details of the shape can be identified more accurately than with the original images. Finally, the properties of regions are numerically evaluated, and the image can be filtered according to certain criteria related on some properties obtaining an image with significant shapes. The structural pattern of the metop includes numerical measures of those significant shapes, for instance, centers of weight and relative distances between them.

4.4 The analysis of Loggia Mathia to Corvin Castle, Hunedoara

Loggia Mathia includes few murals currently damaged. The primary interest is to perform the image analysis at this point in order to obtain the current status of

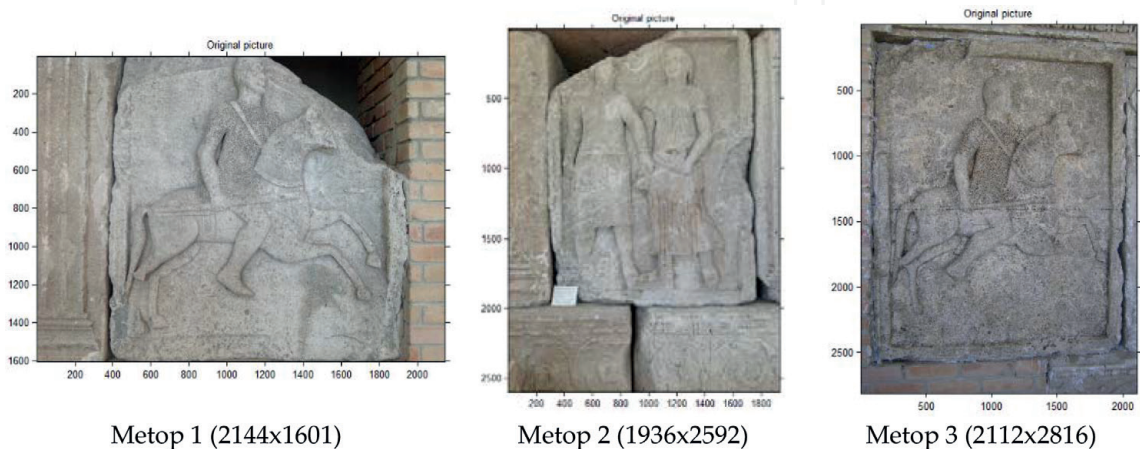


Figure 16.
Three metopes from Tropaeum Traiani Monuments.

the artifact. Then, the data will be used to perform comparative analysis with older images with significantly better quality. The most relevant analysis in this case is chromatics. The original image and the color-labeled regions are presented in **Figure 21**.

The chromatic analysis presented in **Figure 22** reveals the predominance of the red component in RGB spaces of the warm hues in perceptual space. No pure color was detected in the current fresco, but the histogram of the saturation shows a relatively high level of color blending with white. This is explained by the fact that painting is degraded by fading. The luminance of the image has the same distribution as R component which confirms the preponderant visual perception of this component. The color-labeled regions highlight the connected areas of pixels with same color in current images.

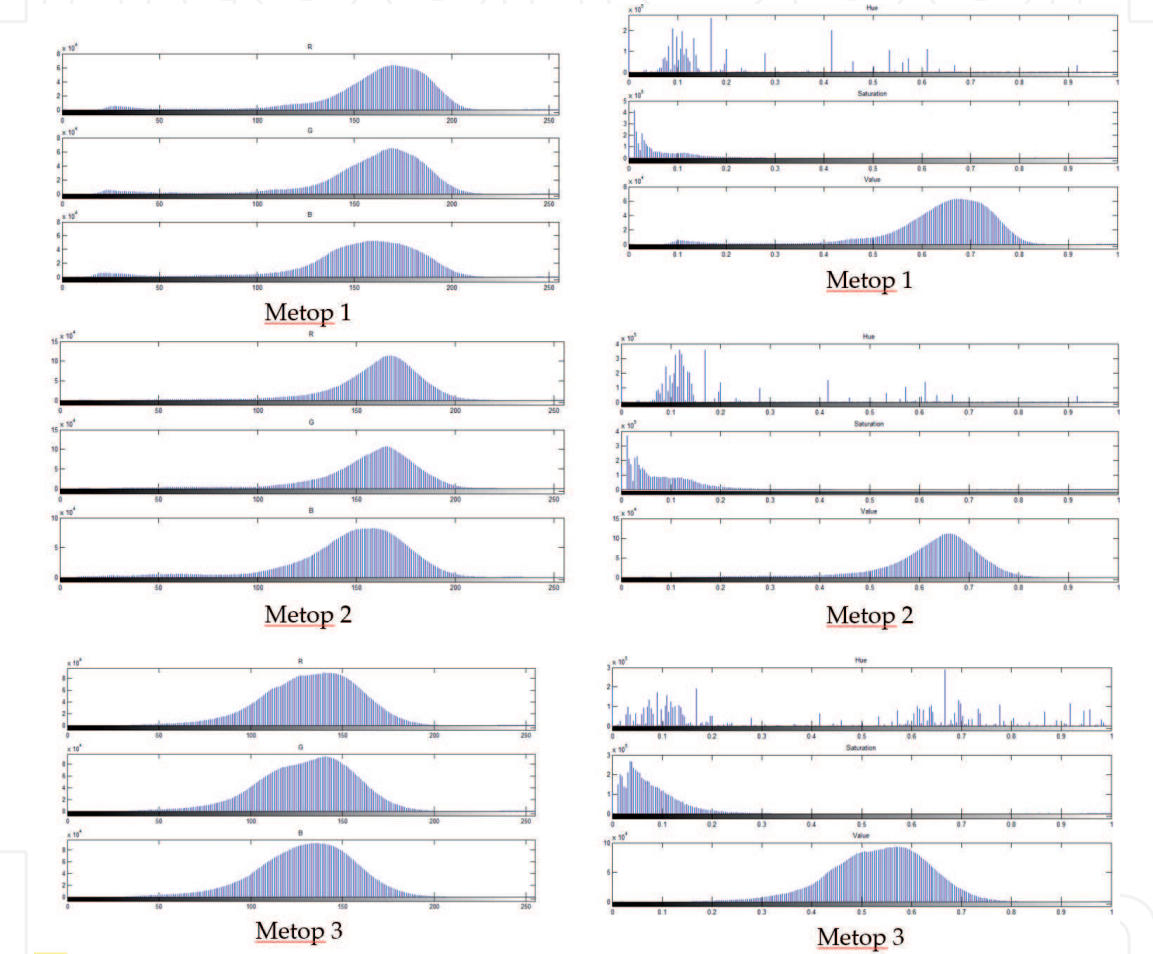


Figure 17.
Chromatic components compared.

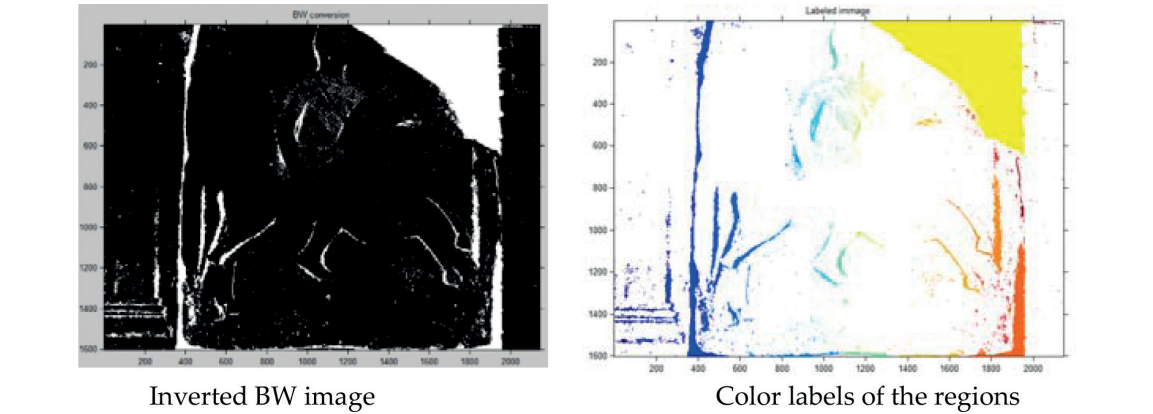


Figure 18.
Metop 1: pattern detected.

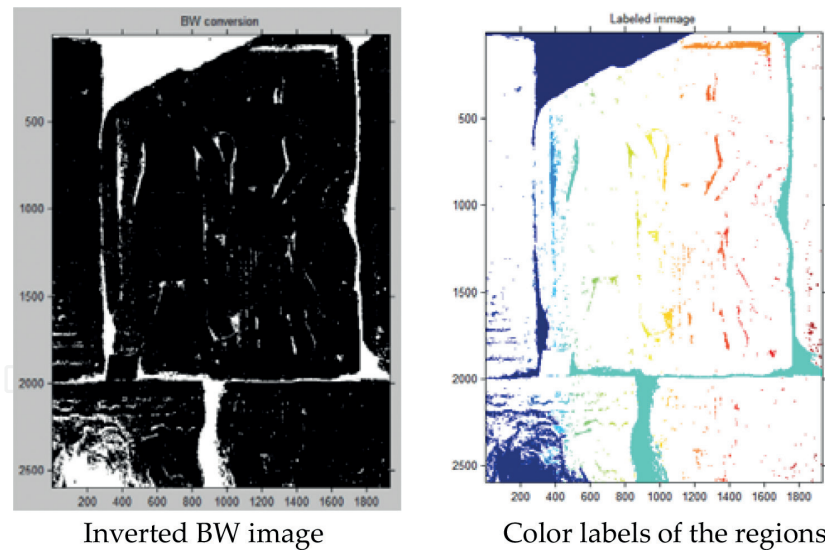


Figure 19.
Metop 2: pattern detected.

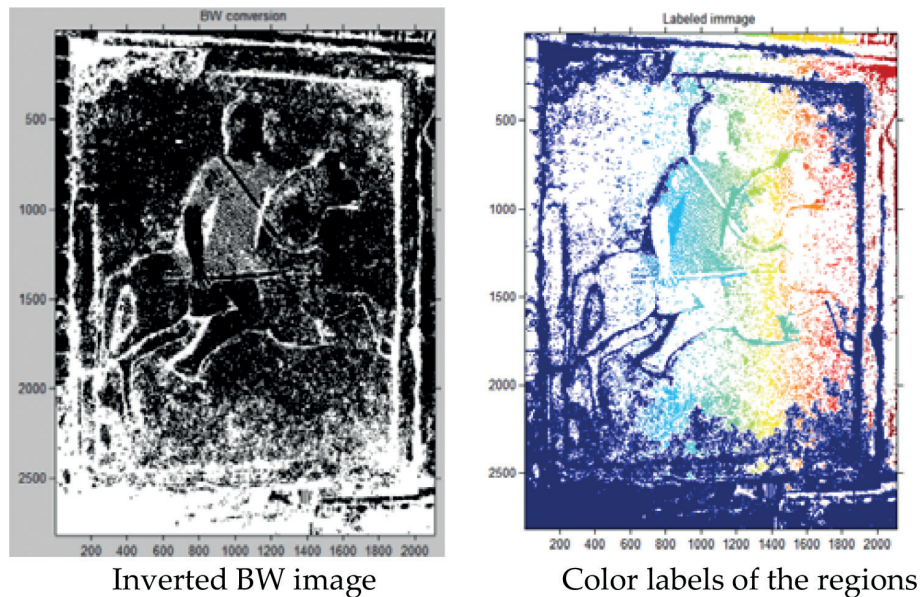


Figure 20.
Metop 3: pattern detected.

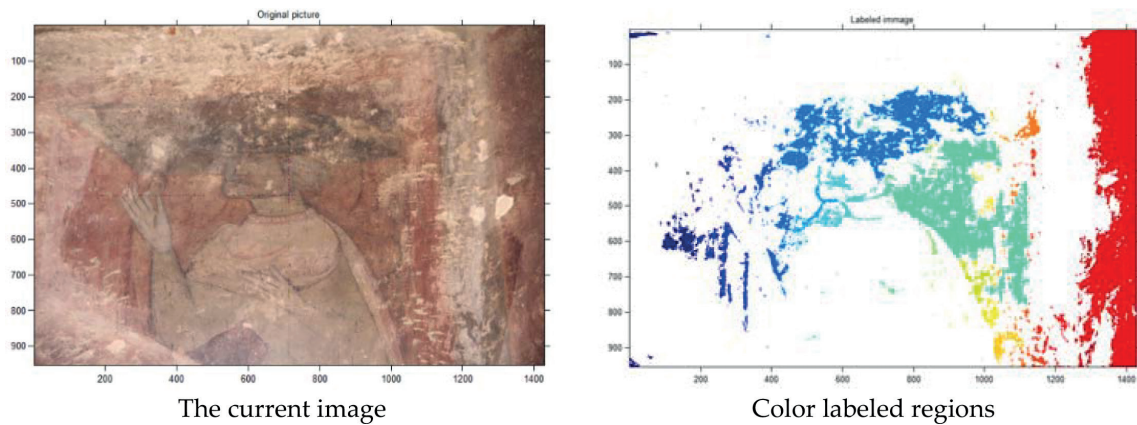


Figure 21.
A fresco of Loggia Mathia.

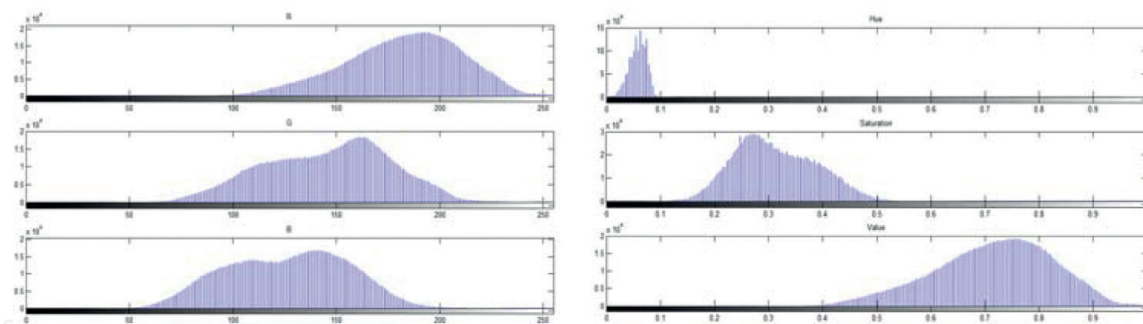


Figure 22.
Histograms in RGB and HSV color spaces.

5. Discussions

The methods discussed above and the examples presented show the applicative potential of image processing techniques in arts, archeology, identity, and cultural heritage conservation. The primary objective of artifact investigation is, in fact, to get the most complete picture of them. Whether it is intended to authenticate the artifact or restoration—preserving it, the structural and chromatic details of the piece are essential for making the decision. The two presented case studies and related examples deal with two categories of artifacts: archeological pieces as three-dimensional objects, respectively, and visual artworks on planar support. In the chosen examples, we have shown that the use of image processing models reveals interesting aspects and peculiarities regarding the chromatic composition and the structure of specific shapes and details. Moreover, formal image analysis tools provide numerical data (indicators) that can be integrated into information structures useful in the authentication, restoration, and conservation of artifacts.

The experiment in the first case study “Tablet from Tărtăria” is based on a picture taken from open sources about which we only know the resolution. The piece itself is a rough disc shape as a flatted calotte with a height (maximum thickness) of less than 1 cm. Its surface is etched with distinctive signs (ancient writing) and generally has local unevenness and rugoses specific to ceramic material. The perceived chromaticity is in the area of yellowish-reddish hues, which is also confirmed by the histogram. Evaluation of the chromatic composition across the image revealed an irregular color distribution (RGB), while detail analysis shows histograms with more concentrated and more regular distributions, close to the Gaussian form. The effect of uniform illumination at the moment of image capture is defining the quality of chromatic distribution.

For archeological artifacts, the chromatic pattern is generally due to alteration/modification of the piece over time. However, the acquisition of images and the evaluation of chromatic components at the time of discovery, at the time of exposure to the museum, and periodically at different time intervals are important for the artifact record. In this way, useful databases can be compiled for the assessment of counterfeiting and the study of changes over time, an important aspect of conservation-restoration work. Formal analysis is equally important for completing the artifact datasheet. The “Tablet from Tărtăria” examined presents essential details in the form of engraved signs. Due to the spatial shape of the piece, it is impossible to detect all the signs by processing a single frontal image. The main states are the deformed projection of inclined or curved surfaces and the effect of uneven illumination. Also, some peculiarities of archeological pieces such as stamps, engravings or bas-reliefs, and even embroidery require a differential analysis on the normal image and the complementary image. As was seen in the analysis of the shape of the engravings, it was necessary to use the complementary black-and-white image. Complex three-dimensional shapes marked by ornamental details characteristic of archeological

artifacts generally impose certain limitations and special conditions when examining them based on images. However, shape analysis can provide trusted data for the artifact records if it is extracted from detailed images taken from the right angles with an optimal lighting scenario. All these conditions must be reproducible on stands with calibrated equipment for optical and photometric determinations.

In the case of flat surface artifacts such as canvas paintings, wall murals, floor mosaics or flat walls, upholstery, or other plain graphic artworks, image processing is very effective. The method is cost-effective, provides a lot of information, is not invasive or destructive to the artifact examined, and therefore is recommended to do it before any other method of analysis.

Image analysis on Claude Monet's "Water Lilies and Japanese Bridge" highlights the relevance of the method for painting works. The chromatic analysis has more relevant details that contribute to the uniqueness of the work and possible to identify the Monet style. The overall appreciation is that the image is balanced in terms of color composition. This is distinguished by the intelligible visual aspect of the component images in both the basic color system and the perceptual system as compared to the original image (see **Figures 10** and **12a–c**).

Compared to the analysis of "Tablet from Tartaria," we find a significant difference in the perceptual space regarding the hue and saturation components. While the archeological artifacts of ceramics have a specific natural color, undifferentiated in the nuances, and saturation planes, Monet's painting contains a shade treasure and reveals an elaborate technique of using colors mixed with white. Histograms in the perceptual color space provide identification data relevant to the "Water Lilies and Japanese Bridge" work, and in the case of the analyzed image detail, the general chromatic characteristics are preserved and in particular highlight the specificity of the execution of some elements by applying clues, for example.

The analysis of the shapes exemplified in the detail in "Water Lilies and Japanese Bridge" reveals the ability of the method to locate distinct regions in the image on a multi-criteria basis. The criterion used by us is "enlightenment and area" that selects all regions in the analyzed image that are brighter than a given threshold and larger than a prescribed value. Practically, any combination of criteria can be formed including chromatic parameters and/or shape properties (see **Table 2**).

The results from *Roman metopes to Tropaeum Traiani Monuments* show data specific to the stone artifacts in color space analyzed. Possible chromatic particularities may be caused by maneuvering or restoring cleaning itself. The shape analysis uses binary image and the color-labeled image in order to obtain information on topology of the artifact. The structural pattern of a metop includes geometrical information that helps restorers to reproduce faithfully.

The fresco from *Loggia Mathia to Corvin Castle, Hunedoara*, is a challenge for restoration. Because the painting is erased, i.e., blurry, the original chromaticity has been severely damaged, and at the same time, some elements of composition have been totally or partially lost. The color-based labeling helps to estimate the original shapes that were painted with the same color. Finally, the restorers have to use the comparative study to choose the colors and to restore the original composition as possible.

The extracted forms can be distinguished by their numerical measures (position, area, orientation, etc.) for the whole painting or its areas. Thus, the structural-chromatic pattern of artifacts in the category of graphical representations on planar support can be constituted by image and shape analysis. Image capture is also important for these artifacts, and great attention has to be paid to lighting. In the case of flat surface objects, there are no theoretical reasons for shading, but reflective and light scattering effects that compromise any image analysis may occur. Consequently, images must be captured at a resolution of at least 1,000,000 pixels

in natural light conditions or near natural light sources, in the absence of concentrated and directional sources that cause reflections and diffuses on the surface of the artifact.

6. Final remarks

Examination of artifacts by optical means and image processing is an elegant and efficient solution. The usability of methods consists in the relevance and the large amount of data obtained by digital image processing. Other benefits such as relatively low costs, avoidance of artifact degradation, the possibility of post-data processing, easy repetition of investigations, productivity of analyses, automatic data processing, obtaining results in a timely manner, and the establishment of data archives relating to works of art and cultural heritage in general.

The prospects for developing these methods are two-way. The first one concerns the development of performance algorithms for image analysis and software applications for their implementation. The second direction is to plan some activities to create archive images of original artifacts and eventually known counterfeits.

The major conclusion is that investigating artifacts through digital image processing is a complementary method of analysis that must be applied with priority before any other invasive rule analysis. Although in some situations, image-based methods cannot substitute for more complex physicochemical analyses that are usually done with material sampling, image processing technology must be extensively integrated into decision support systems for experts and curators in the field of artistic heritage preservation.

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