EVALUATION OF THE PLASMA CLEANED SURFACE OF A HERITAGE WOODEN PAINTING USING IQA METHODS

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Abstract: In this paper a new approach regarding the assessment of the visual efficiency of the plasma cleaning treatment applied in artwork restoration is discussed. The proposed method, which was tested in the case of a wooden painting, evaluates the competence of the cleaning process using image quality indexes based on structural similarity and metrics based on peak-signal-to-noise ratio (PSNR) combined with human visual system (HVS) properties. A systematic comparison between the effectiveness of these metrics and a discussion concerning their performances in the context of evaluating the plasma treatment were conducted.

Keywords: *heritage, plasma cleaning, image quality assessment, structural similarity, PSNR-HVS.*

I. INTRODUCTION

Restoration of cultural heritage items with a material, scientific or spiritual represents an important and demanding activity. According to the restoration specifications [1], it should not only have the effect of improving the physical object, preserving the specific look, but also to ensure its continuity in time. For sure restoration of an heritage artwork is a challenging task that lately applies not only standard techniques, but also engages multidisciplinary efforts, bringing together restoration experts, computer scientists, engineers, and artwork curators [2].

Among the standard restoration methods, plasma cleaning is a novel treatment applied to cultural heritage objects that has been recently reported as an efficient noninvasive method [3]. It is a noncontact method that uses specifically designed equipment and exhibits remarkable cleaning efficiency. The process, which involves surface oxidation realize the cleaning with insignificant loss of surface material removed. The evaluation of the cleaning process has been done so far by visual inspection or by using Energy Dispersive X-Ray Spectroscopy (EDAX) [4], which is an expensive and time consuming analysis. Another method is proposed in [5], where the monitoring and assessment of the treatment process were performed by reflectance measurements from selected areas taken during the removal of soot from acrylic gesso, ink on paper, and varnished oil paint substrates. This method is also time consuming and requires complex and expensive, unlike the method proposed in [6], where the restoration process is evaluated by analyzing the histograms of the test objects imagery.

The method proposed in this paper is similar to the approach reported in [6] and consists in evaluating the cleaning process by using various image quality metrics and indexes for pictures of the test object that were taken at periodic intervals during the cleaning treatment. It is presented a case study for a multi-stage plasma cleaning process of a wooden smoke-damaged painting for which were applied visual quality assessment (QA) methods to images of patches taken in different stages of the treatment, in order to analyze the evolution of the cleaning process.

The paper is organized as follows: in Section 2 the plasma cleaning equipment and the data acquisition setup are described, Section 3 briefly explains the quality assessment metric concept and presents some of the most popular metrics and indexes used in image QA, Section 4 describes the data processing and the experimental results, whereas the last section contains the concluding remarks.

II. EQUIPMENT AND TEST PROCEDURE

The experiments were conducted on an old wooden painting heavily damaged by smoke and other kind of dirt, with a very dark surface. The cleaning treatment of the test object was performed in a vacuum chamber adapted to accommodate paintings suspended in a vertical position inside, between two plates. The vacuum in the chamber was provided by conventional vacuum pumps, the pressure during the treatment ranging from $3.5\ 10^{-4}$ to $7\ 10^{-4}$ bars. Two large parallel plates inside the chamber connected to an HF power supply were used as electrodes to create plasma at a frequency of 13.5 MHz. the temperature inside the chamber was about 35–40°C, and the electric field intensity varied between 20 and 50

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V/cm. The painting to be cleaned was hanged with a thin wire between the electrodes on the positive column area.

The total cleaning exposure was about 180 minutes and was made in stages of 30 minutes. After every treatment stage, the painting was removed from the vacuum chamber and a photo was taken. The image acquisition system consisted of an Olympus E-400 digital camera with 35mm f/3.5 macro lens and four halogen lamps, all placed in a dark room. Position and orientation of the painting, camera and lamps were maintained the same during all experiments. The white balance of the camera has been manually adjusted and kept unchanged during the images acquisition, and also the shutter time and the aperture. The appropriate settings for image acquisition were cross-checked digitally comparing identical areas from the background. Even if the test object was placed in the same position for every photo that was taken, there were slight misalignments that have been digitally corrected.

(a) (b)

Figure1. Images of the painting prior to (a) and after 180 minutes (b) of cleaning treatment.

Figure 1 illustrates images of the wood painting before and after 180 minutes of cleaning treatment. Since the painting was damaged not only by smoke, the plasma cleaning treatment removed only a part of the soot layer that covered the painting in an un-uniform way. Thus the study was focused on measuring how various regions have been cleaned from soot, which in the context of image quality, was interpreted as a distortion, whereas the cleaning process as a kind of filtering operation. For this task several specific areas from the painting were extracted and image quality metrics were applied.

III. METHODS USED FOR IMAGE QUALITY ASSESSMENT

Measuring the visual quality has a fundamental importance in many image processing applications. Traditionally, the QA research has focused on measuring the signal fidelity, i.e. how *close* an image is to a given original or reference one [7]. To a certain extent, in the proposed framework the situation is somehow opposite, i.e., the study is focused on appreciating how *far* the image of the cleaned object to the initial one is. Indeed, this implies that, by cleaning, the distance between the two images increases, a fact that is in general true.

Image QA can be subjective or objective. Objective image QA methods can be generally classified into the following three categories: methods based on the statistic of pixels, such as mean squared error (MSE), root mean squared error (RMSE), or peak signal to noise ratio (PSNR). Although these metrics have some systematic drawbacks and cannot completely comply with human's perception, they are still widely used, as they are easy to compute and independent on images. A second category considers the human visual system properties in an attempt to incorporate perceptual quality measures. This type of metric is based on the psychophysical measurement of the HVS [8]. The last type of methods is based on structural distortion of images. This approach was originally motivated by the observation that natural image signals are highly structured, meaning that the samples of natural images have strong neighbor dependencies, that carry important information about the structures of the objects in the visual scene [9].

In the case of the first class of metrics, many experiments revealed that for two different distorted images having the same PSNR as referred to the same original image, an observer may have very different visual perceptions. A solution to this problem was to incorporate an HVS model, like Contrast Sensitivity Function (CSF) or the luminance masking, to this class of image quality metric. This led to a new measurement more consistent with the human visual perception.

The HVS perceives images by separating them into sub-bands that are selective for spatial and temporal frequency and orientation. In [9], the Discrete Cosine Transform (DCT) has been utilized in contrast masking due to its suitability for certain application and also in modeling the cortical neurons. For a computational model, the combination between the HVS model and the cosine transform imagery must be supported by a mathematical and physical compatibility. In [8] it is assumed that one can achieve compatibility if can correctly combine the HVS model with the cosine transform in a linear system. Hence, under the assumption that for certain classes of image observation [8] the HVS is a stationary linear system, when applying to this system the DCT imagery, at the output one can obtain qualitative information about what a human observer might perceive.

PSNRHVS [10] and PSNRHVSM [11] are two new quality estimation metrics with promising performances, which operate with image intensity information, dividing the image in 8x8 pixels non-overlapping blocks. The modified version of PSNR is:

$$PSNR_{HVS} = 10 \cdot \log(\frac{255^2}{MSE_{HVS}}) \qquad (1)$$

In expression (1), MSE_{HVS} is calculated taking into account HVS according to the approach presented in [8] and given in equation (2):

$$MSE_{HVS} = K \cdot \sum_{i=1}^{I-7} \sum_{j=1}^{J-7} \sum_{m=1}^{8} \sum_{n=1}^{8} (\delta_{PSNRHVS}^{i,j}(m,n))^2 \qquad (2)$$

where *I, J* are the image sizes, $K = \frac{1}{64 \cdot (I-7) \cdot (J-7)}$ and

$$\delta_{PSNRHVS}^{i,j}(m,n) = (a_{i,j}(m,n) - a_{i,j}(m,n)^e) \cdot CSF_{cof}(m,n) \quad (3)$$

where $a_{i,j}(m,n)$ and $a_{i,j}(m,n)^e$ are the DCT coefficients of the 8x8 image block (where *i,j* indices represent the position of the upper left corner of the window) from the original image and from the corresponding block in the distorted image, respectively, whereas $CSF_{cof}(m,n)$ are the elements of an 8x8 correcting matrix proposed in JPEG standard [12], that has been obtained on basis of CSF.

Based on this metric, in [11] a modified version of PSNRHVS, i.e., PSNRHVSM, is introduced. The PSNRHVSM metric takes into account the between-coefficient contrast masking of the DCT basis functions. For each DCT coefficient of an 8x8 block, the model allows to calculate its maximal distortion still not perceived, due to the between-coefficient masking. In this case

$$\delta_{PSNRHVSM}^{i,j}(m,n) = \delta_{PSNRHVS}^{i,j}(m,n) \cdot CM(m,n) \quad (4)$$

where $CM(m,n)$ is a contrast masking metric described in [11].

Instead of using the traditional error summation methods, the index proposed in [13], i.e. the universal quality index (UQI), which belongs to the third class method described above, is designed by modeling any distortion as a combination of three factors: loss of correlation, luminance distortion, and contrast distortion. The term "universal" suggests that the quality measurement approach does not depend on the image being tested, the viewing conditions or the human observer. The index is calculated on samples, using 8x8 sliding windows, because it is more appropriate to measure statistical features locally and then combine them [13]. The $UQI_{i,j}$ of an 8×8 sliding window, where *i,j* indices represent the spatial position of the upper left corner of the window, is defined as:

$$UQI_{i,j} = \frac{4\sigma_{xy}\mu_x\mu_y}{(\sigma_x^2 + \sigma_y^2) \cdot (\mu_x^2 + \mu_y^2)} \quad (5)$$

where μ_x and μ_y are the local sample means of the original image x and the tested image y, respectively, σ_x and σ_y are the local sample standard deviations of x and y, and σ_{xy} is the sample cross correlation of x and y after removing their means (for simplicity the indices *i,j* have been dropped in the formula). For an $M \times N$ image the overall index is given by:

$$UQI = \frac{1}{M \times N} \sum_{i=1}^{M-7} \sum_{j=1}^{N-7} UQI_{i,j} \quad (6)$$

An improved version of UQI is presented in [14], where a structural similarity quality measure SSIM is defined from the perspective of image formation. Since the structure of the objects in a scene is independent of luminance, the influence of it is separated when exploring the structural information of an image. The resulting structural similarity measure SSIM between two images x and y is given by:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1) \cdot (2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1) \cdot (\sigma_x^2 + \sigma_y^2 + C_2)} \quad (7)$$

where C_1 and C_2 are two small positive constants that stabilize each term, so that near-zero sample means, variances or correlations do not lead to numerical instability.

A problem that may occur when applying UQI is the appearance of the "blocking" artifacts in the resulting index map, which is due to the fact that the metric is applied using sliding squared windows. In [14] this issue is solved by using an 11x11 circular-symmetric Gaussian weighting function with standard deviation of 1.5 samples, normalized with unity sum. With this window the quality maps exhibit a locally isotropic property.

IV. RESULTS AND DISCUSSION

The test object used for the experiment was a wooden painting damaged by smoke, dirt, with multiple physical defects, like holes, carvings and cracks in the paint layer. Remember that the total cleaning exposure was 180 minutes and measurements were taken at every 30 minutes.

In the performed experiment, the highlight was on the evolution of the cleaning of the soot layer. As mentioned in the second section smoke dregs are interpreted as noise interfering with the good image signal. Because of the random distribution of the smoke dregs and the poor quality of the test object, it was difficult to estimate a noise model; but nevertheless, for a human observer, at least locally, the effect of soot is perceived as a blurry effect, which covers in a significant quantity fine features like cracks in the paint, light colored patches and other physical defects or features. Therefore, the cleaning treatment had the effect of a kind of filtering operation.

In order to analyze the results of this filtering operation, different relevant patches were selected. Since no prior analysis regarding the composition of the dirt which was covering the painting was performed, the patches selected were those exhibiting clear improvements. Basically, the chosen regions were those where the dark brown dirt was removed, revealing either light colors, and cracks in the paint layer, or carvings and holes in the wood, or other structural features such as wood or paint textures, edges of the objects.

In the framework of image analysis, the improvements consist in an increase of the mean value for light colored uniform regions, higher contrast for dark textured regions and also high contrast and mean value increasing for dark colored regions, slightly textured or containing edges. Through a thorough analysis of the evolution of these measurements, a correlation with the image quality metrics and indexes used to assess the cleaning treatment can be performed. As a result, a comparison between these metrics and indexes in each case would point out which of them is more suitable to be applied.

The image quality assessment metrics considered were those based on HVS properties described in [10] and [11]. Furthermore, the simple PSNR has been applied in the spatial domain, together with the indexes based on structural similarity proposed in [13] and [14].

Table 1 Average values at each stage of cleaning treatment. Reference image: (a) image of the object after 180 minutes of treatment; (b) image obtained in the stage immediately following the current stage.

Time (min)		Initial	30	60	90	120	150	180
Mean value		65.4310	68.6014	63.8335	66.9937	66.0208	73.1825	77.0965
STD		13.8776	18.7836	16.4994	16.4978	17.1359	18.0567	18.4724
PSNR (dB)	(a)	25.1090	27.6826	25.0088	27.1857	26.7690	33.1169	∞
	(b)	28.9170	31.8892	33.7025	35.2687	30.2942	33.1169	-
PSNRHVS (dB) [10]	(a)	20.5005	23.1636	20.6702	22.8446	22.5356	28.8431	∞
	(b)	24.1187	27.4768	29.1200	30.7557	26.0894	28.8431	-
PSNRHVSM (dB) [11]	(a)	20.8024	23.5805	20.8773	23.1639	22.7795	29.8595	∞
	(b)	24.6251	28.1661	30.0301	32.2118	26.5094	29.8595	-
UQI [13]	(a)	0.5236	0.6928	0.6715	0.7359	0.7702	0.8086	1
	(b)	0.6013	0.7686	0.7479	0.7795	0.7955	0.8086	-
MSSIM [14]	(a)	0.7999	0.8603	0.8611	0.8911	0.9059	0.9276	1
	(b)	0.8600	0.9245	0.9252	0.9300	0.9288	0.9276	-

The evaluation of the metrics and indexes were made with respect to different reference images. A first case was when the reference was the grayscale image taken after 180 minutes of treatment, whereas in a second situation the selected reference was the grayscale image obtained in the phase immediately following the current phase. The later scenario was used as a guide in taking the decision whether the cleaning treatment must continue or not. Provided that there was not a significant change in the values from one stage to another, the cleaning treatment was stopped. Measurements were performed for a number of 21 different patches and the average value was calculated for the five metrics and indexes, mean value and standard deviation (STD) at each stage of the process as it can be seen in Table 1.

The metrics proposed for evaluation have values ranging between 0 and infinite for PSNR, PSNRHVS and PSNRHVSM. In this instance, the larger the value of the metric, the greater the similarity between the compared image and the reference one is. Typical values for increased similarity start from 30 dB to 50 dB. For UQI and MSSIM, the values belong to the interval [-1; 1], achieving the maximum value of 1 for identical images.

Analyzing in a first step the values from table 1, it can be noted that the mean value and standard deviation exhibit a random evolution, even though the final results show the expected increase. A similar remark is valid for PSNR, PSNRHVS and the modified PSNRHVSM metric. Also, the values of these metrics are very small compared to the interval for which the images are considered to be almost similar. This last observation underlines the obvious statement that the visual quality of even the final resulting image is far from being considered the maximum one from a human visual perspective.

Figure 2. (a) UQI=0.99, MSSIM=0.99, PSNR=43.01, PSNRHVS=37.18, PSNRHVSM=37.75; (b) UQI=0.99, MSSIM=0.99, PSNR=38.26, PSNRHVS=32.85, PSNRHVSM=33.17; (c) UQI=0.99, MSSIM=0.99, PSNR=39.87, PSNRHVS=35.09, PSNRHVSM=33.52; (d) UQI=0.99, MSSIM=0.99, PSNR=44.99, PSNRHVS=39.20, PSNRHVSM=39.85; (e) Reference image: UQI=1, MSSIM=1, PSNR=∞, PSNRHVS=∞, PSNRHVSM=∞.

Additionally, this characteristic reveals that these metrics are highly sensitive to noise. In order to test this sensitivity four distorted images of the same reference image have been considered, as illustrated in Figure 2. The distorted images are affected by a small black spot placed in different positions. Measurements performed on these images exhibit very close values, excepting the values for the three PSNR metrics, which are very different, even in the presence of a small distortion. In addition, the difference depends on the location of the distortion. This is a result of processing the images with fixed non-overlapping 8x8 blocks, in which every block equally influences the quality metric. Hence, an independent block might produce sharp changes that greatly affect the subjective quality perception, depending on how salient the distorted block is in the reference image [15]. Thus, for images 2.a and 2.d, where the distortion is placed in dark regions, the values of these two metrics are larger, which suggests that the degree of similarity is more reasonable.

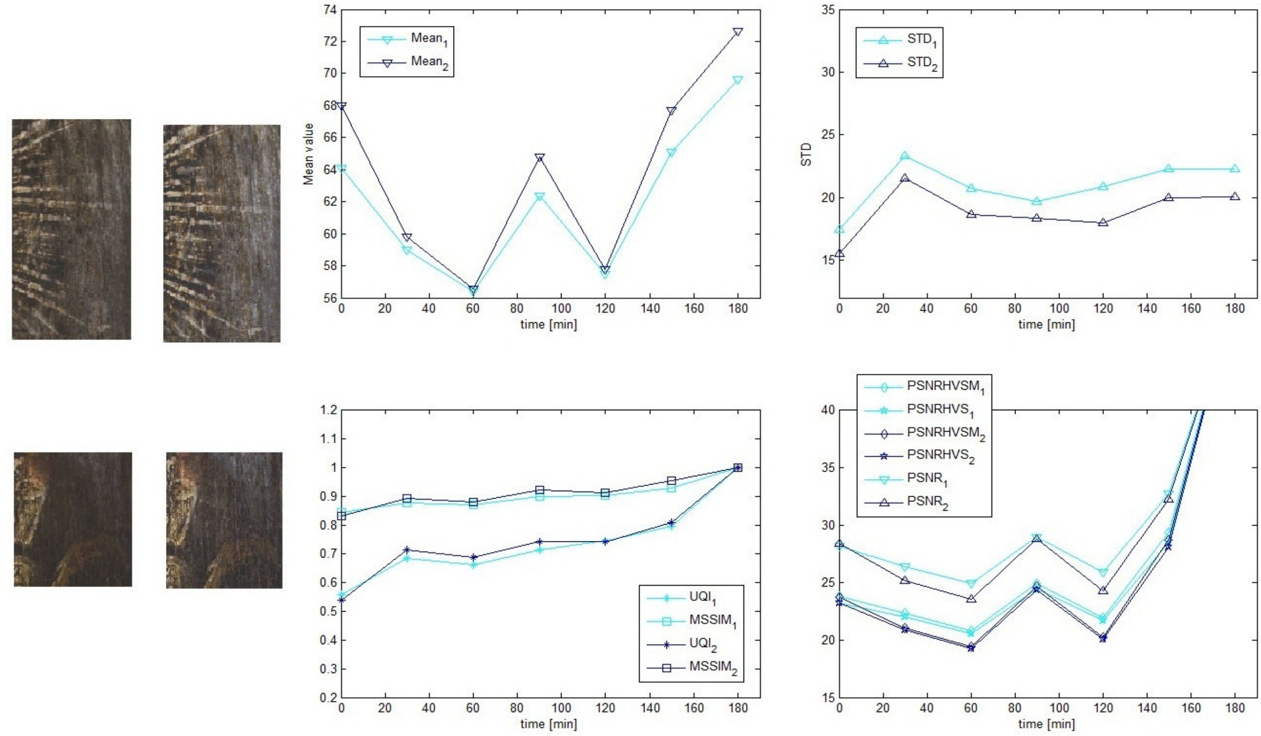
Another subjective remark refers to the fact that the soot layer covers the paint with a dark brown shade, which may affect the hue of colors, and thus a more proper analysis of the HVS perception based metrics should be made in a color space.

Even if the PSNR values proved the fact that the resulting image is far from being considered acceptable for a human observer, in this paper the focus is on observing a clear removal of the soot layer, which modifies in fact the structure of the images. Under these conditions, the next two methods, which are based on the structural similarity, are more suited to assess the cleaning treatment.

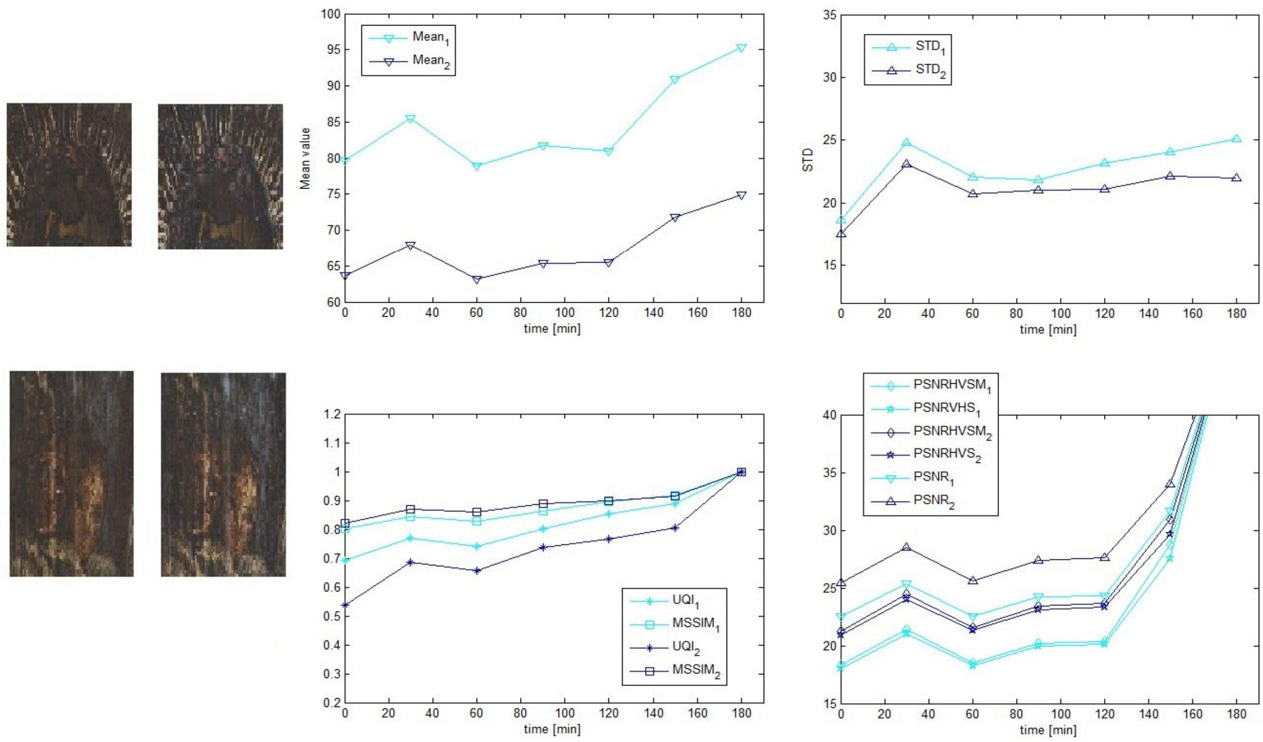
Despite their simplicity, the UQI and the MSSIM scores exhibit a monotonically evolution across the treatment stages, because these methods are less sensitive to luminance-shifting and contrast stretching, which generally do not degrade the image structure. Furthermore, according to the results from Table 1, these metrics have values very close to the maximum one. Also, the second type of measurement depicted in Table 1, which for the PSNR related metrics had again a random evolution, was more relevant for the structural similarity indexes. In this case, the MSSIM index, proved to be more stable with respect to mean value and STD fluctuations. The nearly constant value of the MSSIM index for the last two treatment stages shows that continuing the cleaning treatment would not bring visible improvements. Analyzing the measurements made for the selected patches, it can be deduced that, for each patch, there was a similar parameter evolution during treatment, with the exception of the mean value (Figure 3). In this instance, there were distinguished two types of evolutions, but analyzing the images it was impossible to establish a general and consistent argumentation, which would explain the correlation between the specific patch and the type of exhibited variation.

In Figure 3 there are given two examples for each type of patch. Following the graphical evolution of UQI and MSSIM, it can be concluded that these indexes are insensitive to the random evolution of the mean and the standard deviation values. Only a slight dependency can be observed after the first treatment stage, when the mean and the STD have unexpected evolutions. This issue is less noticeable in the case of the MSSIM index, which separates the luminance influence, showing an almost monotonically evolution throughout all the cleaning treatment stages.

As far as the PSNR related metrics are concerned, it is straightforward to remark that the curves of these metrics have a similar behavior to that of mean value. If for the simple PSNR and for the PSNRHVS, respectively, this result is expected, for the improved version PSNRHVSM, the dependency on the mean value is due to the fact that the between-coefficient contrast masking of the DCT basis functions is calculated under the assumption that each DCT coefficient of an image block masks to some extent any other block coefficients, excepting the DC coefficient that corresponds to the block mean luminance, thus the mean value substantially influences these metrics values.



(a) First type of patches



(b) Second type of patches

Figure 3. Examples of patches and their mean, STD and image quality metrics and indexes evolutions; (a) first class of patches; (b) second class of patches.

V. CONCLUSIONS

In this paper was proposed a new low-cost, efficient method to assess the plasma cleaning treatment applied in heritage objects restoration. The evaluation of the cleaning treatment was realized by applying image quality metrics and indexes on different patches, which were cropped from the pictures of the test object. Furthermore, a systematic comparison between the performances of the considered methods is presented, based on the computation of the statistical mean and standard deviation values, and thus establishing which the optimal procedure in this context is.

The experimental results proved that the indexes based on structural similarities ore more suited to the assessment of the soot cleaning treatment, the presence of this layer on the wood painting being similar with a noisy distortion, which affects mostly the structure of the objects from the scenes. It can be concluded that in case of the HVS based assessment methods, a more correct approach would be to apply them in a color space, given the fact that the presence of soot randomly influences the color hues.

The results yield that the PSNRHVS and its improved version PSNRHVSM lead to very small values, because these metrics are very sensitive to noise presence, especially if the noise is located in salient regions. Furthermore, the PSNR based metrics have a strong dependency on the mean value, which had an unpredictable random evolution during the treatment. On the other hand, the less sensitive to luminance-shifting and contrast stretching, UQI and MSSIM indexes experienced a monotonic evolution during the treatment process, reaching a closer value to the maximum one. Due to the random evolution of the PSNRHVS and the PSNRHVSM during the treatment process, it can be stated that these metrics cannot be reliably applied for the plasma cleaning assessment. In this scenario, the MSSIM method and, to a lesser extent the UQI technique, are more appropriate candidates.

As a conclusion, the indexes based on the structural similarity proved to be more suited to evaluate the image quality, not only in this context, but also for the general purpose of image quality assessment. Without employing an explicit HVS model, these indexes have a strong ability to measure structural distortions. The low performances of the PSNRHVS and the PSNRHVSM are a consequence of the fact that there does not exist a well-defined mathematical framework for the HVS model. Also, the error summation methods, applied in various formats such as pixel values, weighted pixel values, weighted DCT coefficients, are considered to be an inappropriate mathematical form for image quality assessment, as it is impossible to estimate the correlation between two images by simply differentiating them.

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