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A cockpit of multiple measures for assessing film restoration quality☆

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A B S T R A C T

In machine vision, the idea of expressing the quality of a films by a single value is very popular. Usually this value is computed by processing a set of image features with the aim of resembling as much as possible a kind of *human judgment* of the film quality. Since human quality assessment is a complex mechanism involving many different perceptual aspects, we believe that such approach may scarcely provide a comprehensive analysis. Especially in the field of digital movie restoration, a single score can hardly provide reliable information about the effects of the various restoring operations. For this reason we introduce an alternative approach, where a set of measures, describing over time basic global and local visual properties of the film frames, is computed in an unsupervised way and delivered to expert evaluators for checking the restoration pipeline and results. The proposed framework can be viewed as a car or airplane *cockpit*, whose parameters (i.e. the computed measures) are necessary to control the machine status and performance. This cockpit, which is publicly available online, would like to support the digital restoration process and its assessment.

1. Introduction

Film restoration is a complex process devoted to rescue and preserve the content of degraded films. Such a process should account for many different aspects, such as the physical and chemical features of the film, the typology of the film, the cultural context in which the film has been produced, and the target audience. Therefore, film restoration involves many different fields of study, like philology, history, chemistry, physics, optics and computer science. The plethora of different aspects that must be taken into account and the lack of codified rules and shared methodologies [3,10] make film restoration a very challenging task [8,9,48].

Digital Restoration, DR, applies two main steps: the “DR” *per se*, which minimizes or even removes artifacts like flickering, scratches, dust and stabilizes the scenes ([14], and the “Color Correction”, which handles colour alteration and fading. While mostly used restoring software employ automatic or semi-automatic algorithms for DR, the color correction task is still mainly manually performed by experts via semi-automatic methods, though unsupervised algorithms have been recently proposed [5,36,37,46].

DR presents several advantages with respect to the analog restoration. First of all, DR allows to test and study different, eventually automatic, restoration procedures, without intervening on the analog support with the risk to damage the original data. Second, the different solutions provided by DR can be compared, giving the possibility to choose the best one or to combine the different steps to obtain the desired result. Third, the use of image enhancers and color grading algorithms working independently on the color components enables a color correction which is more effective than that provided by the procedures generally employed in analog restoration, where the color is treated as a single entity [4,11]. This is the case of the yellowish effect due to the aging, and mainly affecting two image components in the RGB color space.

Regardless of the way the movie is restored, the quality of restored movie is an important task, generally performed by curators and experts based on their personal experience, expertise, and skills. The assessment of the intermediate results produced by each step of the restoration process, allows the expert to assess the restoration pipeline deciding each time if a processing step is effective, and must therefore be kept, or if it must be changed or removed. Therefore, the intermediate assessments, as well as the assessment of the final result, are important for they allow to define the optimal restoration pipeline. Unfortunately, quality assessment of restored movies is a not “well defined” task, for agreed

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Table 1
Title of the films, unique ID, cardinality, principal characteristics, and the exploited enhancers with the values of their parameters.

Film	ID	Cardinality	Main Characteristics Before Restoration	Applied Enhancers (Parameters)
Fiat 508 (1931)	1	888	Black and White movie Flickering Dust and Scratches Silver Fading	
Phoenix (Manual) + ACE ($r(x) = 2x$)				
La lunga calza verde (1961)	2	363	Animation Movie Colour Fading	STRESS ($M = 200,\ N = 20$)
La Ciudad en la Playa (1961)	3	125	Super 8 movie Strong colour fading Dust and Scratches	RSR ($N = 200,\ n = 20$)
I funerali delle vittime della strage di Piazza Loggia (1974)	4	261	Super 8 movie Colour fading Dust and Scratches	
Instability	Phoenix + DaVinci Resolve ACE ($r(x) = 5x$) CLAHE applied on L^* channel ($N = [0, 01]$)			

quality standards are still lacking. At the state of the art, film quality assessment is generally performed by analyzing features describing either single frames or inter-frame relationships, and proposing one or several numerical estimates of their quality over time. In this way, film quality assessment becomes a problem related to frame (image) quality assessment. Anyway, modeling the features that concur to the Image Quality (IQ) assessment is a difficult task, still under investigation [29] and for which a global standard has not been defined yet.

Based on the aforementioned considerations, in this work we present an alternative framework for supporting expert users during their objective assessment of restored movies. This work extends that proposed in [32] by including a more comprehensive state of the art, explaining in depth the idea at the basis of the cockpit, and providing and discussing the Web application *MoReCo* which allows employing the cockpit and evaluating its performance. The proposed set of no-reference objective measures is capable of describing the level of *readability* of the visual content of the film and of quantifying the perceptual differences between the original and restored films. The term *readability* here refers to the human understanding of the observed scene and of its details. We model this readability by five popular image features, most of which already employed in computer vision to assess the performance of an image enhancer (e.g., [21], [19]): the brightness, the contrast, the color distribution entropy, the local color variations of each frame, and perceptual intra-frame color changes.

Our framework basically acts as *the cockpit* of a machine, as a car or an airplane. The cockpit computes measures that can be viewed as the parameters controlling the video status and the performance of the restoration pipeline. As it happens in the cockpit of an airplane, the quality measures are kept separated, and the understanding of their different semantic meaning (the conditions of different characteristics of the airplane) is left to expert users (the pilots), who merge them and form by themselves a global judgement about the system performance (the airplane) by also considering the current needs and their experience. Unifying the quality measures in a single one may cause information loss and would hide the causes of the obtained assessment number. As a result, if the users wanted to improve performance, they would not know which airplane characteristics to modify. Similarly, in our application we let any expert user analyze the provided measures separately, and interpret them eventually considering other non-visual features, as content, historical period, film emulsion, public, that may even change over time. The basic idea behind this work is to put, at the centre of the data interpretation process, the users and not the computer programs because this will assure their active and engaged participation and will exploit their expertise in the field [1]. To show the usefulness and reliability of the cockpit, and to lay the foundations for a future more complete *film-assessment cockpit* exploiting and integrating more film-description measures, we tested the framework on different scenes of films restored through one or more among five image enhancers.

The work is organized as follows: in Section 2 we shortly describe the background and the rationale behind our work; Section 3 describes the cockpit; in Section 4 we recall the enhancers employed for the restoration of the video used in the experiments; in Section 5 we describe the analyzed films (see Table 1) and the obtained results; finally, in Section 6, conclusions and future works are reported.

2. Image quality

As claimed in Section 1, the use of only one value for movie quality assessment may not suffice to evaluate effectively the IQ, since the metric often accounts for few visual cues. This point emerges clearly in the wide survey reported in [27] and [29], where authors compare different assessment metrics, by reporting the number of performed tests and the number of persons involved in the tests. This very careful and massive work underlines the inner complexity of IQ assessment, and the difficulties of fitting and compressing it in a single value.

In film restoration the quality control is always made and supervised by the curator, who defines the restoration pipeline based on the consecutive results obtained by the intermediate steps of the restoration process. The assessment of the restoring results is based on the curator's skills and experience and controls are made comparing the restored films with the original film or with films from the same historical period, when the original is missing. The lack of trustworthy reference in film restoration is one of the main limits in the application of the so called Full-Reference (FR) and Reduced-Reference (RR) metrics [29]. FR methods assess the quality of restoration by comparing the restored image to the original reference image, while RR methods compare some features computed from the restored image to those computed on the original image.

Considering the classification proposed by [29], some examples of FR metrics are: mathematically-based assessments, like Mean Square Error and Peak Signal to Noise Ratio; low-level metrics, like Spatial-CIELAB [51]; high-level metrics like Structural SIMilarity [52] and Visual Image Fidelity [45].

Unfortunately, since even films stored in perfect conditions are subject to decay and aging, having an original reference of a film from the age in which it was shot is really hard. As a consequence, No-Reference (NR) metrics, which do not need any reference, are the most suited for this purpose. These metrics are mostly designed for capturing one or more predefined specific distortions types [26]. They are widely used for evaluating the performance of image compression, dynamic monitoring and adjustment of IQ, image restoration and enhancement processes, and thus they allow optimizing the parameter settings of denoising, deblurring and sharpening algorithms. Some examples are: Blind Image Quality Index [22], Distortion Identification â based Image Verity and Integrity Evaluation [24], Blind/reference less image spatial quality evaluator [23].

Nowadays, many NR metrics are based on the use of neural networks and, synthetically, computed a quality value based on the "experience" made on a set of training images, e.g., [13]. Such methods are trained on commonly used test images not effectively representing the range and variety of different scenes a director or artist may have recorded [31]. Furthermore, the film bases and technologies used during the years, such as Technicolor, Kinemacolor, Tinted and Toned films, present specific features and colours that differ fundamentally from a natural pristine image. Therefore, in the current stage, the subjective assessment made by domain experts cannot be replaced by a single IQ measure, because the restoration process involves different enhancements on specific film features that cannot be synthetized by one metric. Moreover, since IQ criteria may change according to external non-visual requirements, like aesthetic issues, content, and/or public, when working with machine learning methods, the non-informatic expert user must relabel the training set each time the quality requirements change.

3. The cockpit

Based on the considerations expressed in Section 2 we propose to replace the commonly used unique score for IQ assessment with a multi-score one. Precisely, our cockpit consists of five no-reference, objective measures that are computed frame by frame and that capture basic visual perceptual features related to the image readability.

Specifically, let I be the frame of a film expressed in the RGB color space, L^* the luminance channel of the image I expressed in the $CIEL^*a^*b^*$ color space, with a gamma of 2.2 and the D65 as reference illuminant. The measures included in the cockpit are the following:

1. mean intensity of all the pixels in each channel of I (mI): this results in a 3D vector $mI = [mR, mB, mG]$.
2. mean luminance (mL): it is the mean intensity of all the pixels in channel L^*.
3. Multi-Resolution contrast of L^* (MRC) [28,35,44]. The local contrast $lc(x)$ of L^* at pixel x is the mean value of the L^1 distances between $L^*(x)$ and the intensities of the eight pixels surrounding x in the 3×3 window centered on x. The mean local contrast of L^* is the average of all $lc(x)$ for each pixel x in L^*. The multi-resolution contrast MRC of L^* is the average of the mean local contrasts of a set of images $L^*_0, \ldots, L^*_K$ $K(>1)$ obtained by sequentially scaling L^*, with $L^*_0 := L^*$. In this work, $K = 4$ and the scaling factor applied to L^*_i is computed so that the minimum dimension of the image L^*_4 is not less than 25 pixels, while the size of the three images in between L^* and L^*_4 is uniformly distributed between the sizes of L^* and of L^*_4.
4. Deviance from Histogram Flatness (HF): measures the entropy of the distribution of L^* as the L^1 distance between the histogram $H(L^*)$ of L^*, normalized to sum up to 1, and the uniform probability density function over the range of I, which typically is [0, 255]. Note that, in its original formulation [20], the HF was applied to the R, G, B channels separately. However, in this paper, similar to [19], we apply it to the image brightness.
5. Coefficient of Local Variation (CLV): it is the mean value of the relative standard deviations $\sigma(x)$ computed at each pixel x of L^*. In particular, we remember that $\sigma(x)$ is the ratio between the standard deviation and the mean of L^* in a 9×9 window centered at x, where the mean differs from zero. In this computation, the mean of L^* is of course assumed to differ from zero, and the neighborhood of pixels adjacent to the image border is assumed having the same value of the nearest image border. The value of CLV measures the local dispersion of the probability distribution of L^* and relates information of brightness and contrast.
6. Color Difference (ΔE): it is the intra-frame normalized sum of color differences $CIE\ \Delta E$ which is the L^2 distance between two consecutive frames in the perceptual color space $CIEL^*a^*b^*$.

The cockpit measures are very popular and basic perceptual features. They have been chosen among many others since they offer interesting and intuitive information about the quality of an image and, according to our thesis, they must be considered all together in the quality assessment process. In particular, we note that the values of *mL, MRC, HF* effectively correlate with the human judgement, as shown by the subjective experiments reported in [18] and [19]. In such experiments, a group of volunteers were asked to look at a set of pairs (J, E_J) of images where E_J is an enhanced version of J, and to choose the image they considered the most readable.

The responses revealed that in about the 60% of the tests, the enhanced images, having a higher brightness and contrast and a more uniform color distributions than the input ones, were preferred. When the images J and E_J were similar, in about the 16% of the cases, the volunteers did not express any preference. In the remaining 24% of the cases, they preferred the input image, even if it appeared dark and with poorly visible details. This last outcome was mainly due to aesthetic issues or to the presence of noise that was erroneously emphasized by the enhancer. In the cockpit, noise is estimated by the measure CLV that accounts for local intensity variations.

The value of ΔE is known to be related to the human perception of the colors [50]. The time analysis of ΔE may reveal the presence of flickering or abrupt changes of the scene color, that could indicate the presence of burned frames. In particular, the more slowly ΔE changes, the lower the flickering.

It is important to note that exact values of *mI, mL, MRC, HF, CLV*, ΔE for identifying a readable image/video do not exist since these measures depend on the image/video itself. For instance, very high values of *mI, mL* do not necessarily correspond to a readable image, since they could describe a saturated image, where the details are completely lost. The values of *MRC, HF* and *CLV* are hence of great importance to evaluate the status of the IQ, but they need to be analyzed also upon the content of the film. Here the intervention of the expert users is essential to decide if and how to restore the visual material.

Our approach differs greatly from the recently spreading approach, where some features describing image qualities are merged into a unique measure of visual quality. A notable example of such approaches is presented in [13], where seventeen IQ measures are merged through a support vector regression model [7], trained on a set of images automatically generated and labelled. Though interesting, this approach has one main weakness due to the fact that the user is provided with a unique quality measure and the motivations for the quality assessment results are not provided. As a result, if this single value says that the IQ is poor and the users want to improve it, they will never be able to understand which frame characteristics have caused the achieved quality measure, unless they re-compute by themselves the seventeen measures, in search for the image features to modify. Moreover, as already mentioned in Section 2, the machine learning approaches must cope with the problem of training videos taking into account also non-visual features that may change over time.

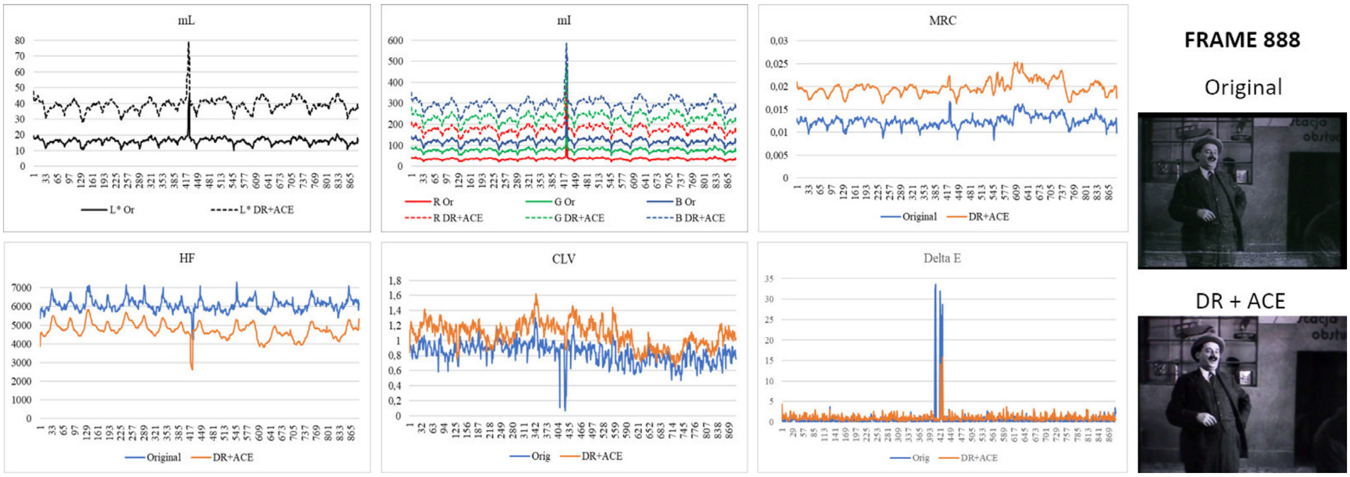

Fig. 1. Plots of *mL, mI, MRC* (top), *HF, CLV* and ΔE (bottom)for frames of the video "Fiat508″.

4. Image enhancers

This Section describes the algorithms used for film restoration. Precisely, in Section 4.1 we briefly report three Retinex inspired spatial color algorithms, namely the Automatic Color Equalization Algorithm (ACE, [40]), Random Spray Retinex (RSR, [34]), and Spatio-Temporal Retinex-Inspired Envelope with Stochastic Sampling (STRESS, [15]); in Section 4.2 we describe the popular Contrast Limited Adaptive Histogram Equalization (CLAHE, [25,53]) method. We have chosen these algorithms among many others since ACE, RSR, and STRESS have been already employed for restoring, while CLAHE is very popular. Anyway, the cockpit might be applied to any video restored by means of any other algorithm.

4.1. ACE, RSR, and STRESS

ACE, RSR, and STRESS belong to the family of Spatial Color Algorithms (SCAs) [42], which recompute wavelength/energy arrays into calculated color appearance arrays, or preferred color enhancement arrays, according to the spatial distribution of pixel values in the scene. Importantly, SCAs have the interesting property of being unsupervised, meaning that they automatically adjust color and contrast [42]. ACE, RSR, and STRESS belong to the Milano-Retinex family [33], proposing alternative implementations of Land's Retinex model [16,17] and therefore inherit the property of local filtering. Moreover, as the original Retinex algorithm, when applied on RGB images, ACE, RSR and STRESS work separately on the three color channels. For each target pixel p_t, with intensity $I(p_t)$, ACE computes a novel value by firstly considering the spatial color distribution of pixels p_{neigh} located in a circular neighborhood, of radius R, centered on the target pixel p_t. This local processing, exploits a function $r(\,\cdot\,)$, whose input is obtained by reworking the pairwise differences $|I(p_t) - I(p_{neigh})|$, weighted by the scaled Euclidean distance between the two pixels. After the local processing, a global rescaling maximizes the image dynamic. ACE has been successfully applied for fine art print [43], wall painting [12] recovery, interfaces assessment [39], and digital film restoration [6,38,41].

RSR computes the new pixel intensity of the target pixel p_t by considering a 2D-shaped circular neighbourhood of radius R around p_t. The intensity of p_t is rescaled with the maximum intensity value chosen by sampling the neighborhood of p_t by N random sprays, i.e. N sets of M pixels randomly sampled around p_t with radial density, and averaging the reciprocals of the maximum intensities of the sprays. RSR has proven to be effective for color movie restoration [36].

STRESS inherits from RSR the idea of a local white reference, but implements a very different pixel value stretching. Rather than considering only a local reference white for computing a "compensated" value for each target pixel p_t, it also considers a local reference black, so that the intensity at p_t is stretched between these references. For each target pixel p_t, it uses the same sprays generation of RSR, where it stochastically samples M pixels for N times. The new value for p_t is then stretched between two values $E_{\min}$ and $E_{\max}$ computed by re-working respectively the minimum and maximum intensities of the N random sprays sampled around p_t. STRESS has been successfully applied for spatio-temporal color correction of movies [47].

4.2. CLAHE

Developed as an advancement of the Adaptive Histogram Equalization [30], CLAHE is a spatial domain method. CLAHE splits the image into *NxN* not overlapping regions, also called tiles, where a mapping function is derived as the cumulative distribution function of the clipped histogram of the tile. Clipping allows to avoid over-amplifications in near-constant regions where the histogram is mostly concentrated. Since the mapping is appropriate only for the pixel at the center of the tile, the mapping for each other pixel p is obtained by interpolating the mappings of the tiles with center pixels closest to p itself.

5. Results

To measure the reliability and usefulness of the proposed cockpit, we analyzed four frame sets extracted from four different films. The cardinality of the frame sets, their visual characteristics, and the techniques used for restoration, are different. Precisely, the employed enhancers are: ACE, RSR and STRESS, CLAHE, and two commercially available software providing techniques for manual film restoration, which are the Phoenix software [49], and the DaVinci Resolve [2]. ACE, RSR, STRESS, Phoenix, and DaVinci Resolve were applied on the image frames expressed in RGB color coordinates, while CLAHE was applied only on the L^* channel of the image transformed into the $CIEL^*A^*B^*$ color space.

The film restorations have been performed during the past years at the MIPS Lab of the Computer Science Department at the University of Milan, Italy, for research studies. Table 1 reports the title of the films from which the frame sets were extracted, the frame-set cardinality, the characteristics of degraded frames before restoration, and the list of applied enhancers and their parameters.

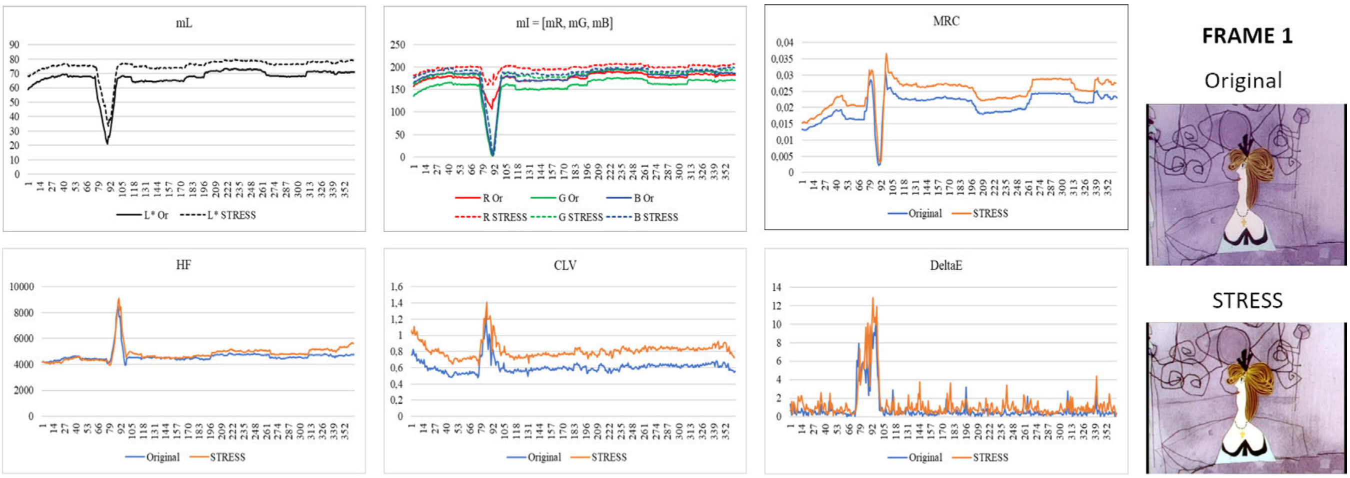

Fig. 2. Plots of *mL, mI, MRC* (top), *HF, CLV* and ΔE (bottom) for frames of the video "La Lunga Calza Verde".

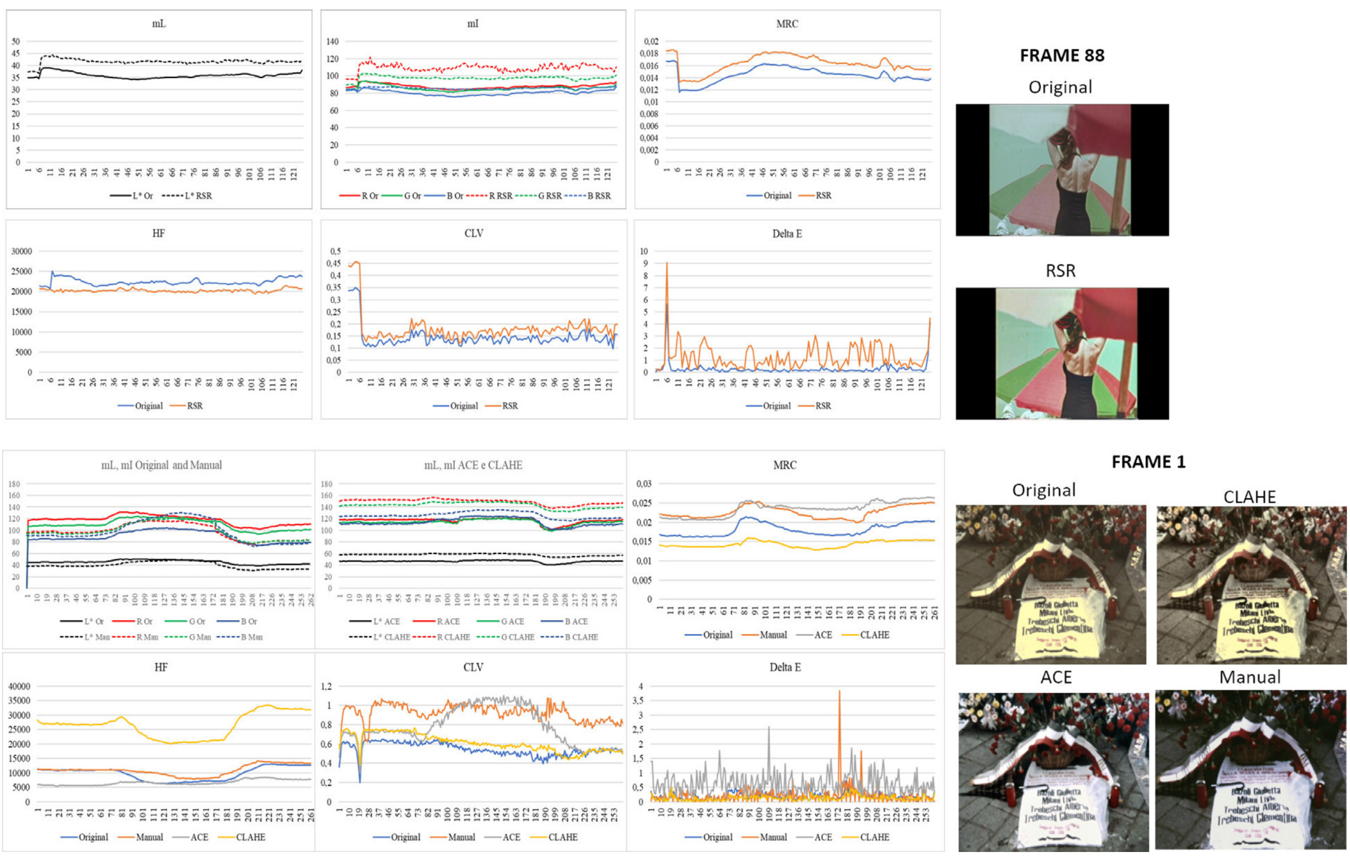

Fig. 3. Top panel: all the plots produced by the cockpit for film "La ciudad en la playa". Bottom panel: all plots produced on the restored film: "I funerali delle vittime della strage di Piazza Loggia", by ACE, CLAHE, and manual restoration.

Note that ACE and STRESS use as neighborhood the whole image. Figs. 1, 2 and 3 show some examples[1]

The film "Fiat508〃 (see Fig. 1), is black and white and has the 435th frame completely burnt and white, which causes a strong flickering. The per-frame $mI = [mR, mG, mB]$ and mL plots show that DR and ACE increase the frame brightness; moreover the mR and mG values have been made similar by ACE; nevertheless, both the enhancers still leave a blue dominant in the whole scene. At the same time, the per frame *MRC* plot indicates that contrast has been increased. The value of *HF* is increased in the restored film, which is probably due to the contrast increase resulting in the increase of the histogram entropy.

In "La Lunga Calza Verde" (see Fig. 2), the analyzed scene presents an animation in which the scene is uniformly colored in red, around the 80th and 90th frames. This characteristic is visible in the *mI* plot, where the *mB* and *mG* curves strongly decrease in correspondence to those frames. STRESS increases the intensities of the three RGB channels, remarkably faded in the original film, and results in a comparable difference between the *G, B* and the *R* channel. Moreover it creates brighter and more contrasted frames, as shown by the plots of *mL, CLV* and *MRC*. Simultaneously, the his-

[1] Figures with higher dimension are shown in the Supplementary material.

togram flatness is decreased, and the ΔE values are comparable, suggesting that no flickering has been introduced.

The film “La Ciudad en La Playa” (see the top panel of Fig. 3) presents a very strong colour fading and the application of RSR was a first attempt to restore the original colours of the film. Although RSR increased the frame luminance *mL*, it increased both the difference between the R, G and B channels and the inter-frame variability of the R channel. The values of *MRC, HF*, and *CLV* have been increased, indicating that the restoration has revealed more details. The increase of ΔE and the emphasized difference between the mean of R, G, and B values, suggests that some color unbalance and flickering might have been introduced. In this case, the cockpit allows to outline the pros and cons of the restoration, and lets the user decide whether to proceed with the restoration at hand or start again using other techniques.

The last application of our cockpit is made on “I funerali delle vittime della strage di Piazza della Loggia” (see the bottom panel of Fig. 3). This Super8 documentary was restored through three different enhancement methods: manual restoration by Phoenix and Da Vinci, ACE and CLAHE. Manual restoration decreased the luminance *mL* and increased the contrast *MRC*. ACE produced *mL* values close to the original video, while CLAHE greatly increased the *mL* values. Considering the higher contrast *MRC*, the performance of Manual restoration and CLAHE are similar, while ACE produces the best results. This example shows that different enhancement methods produce different results. In this respect, the cockpit may be a valuable tool to guide and support the work of the restorer in identifying the method that provides the best results for the final purpose.

To let any user experience the proposed approach, we implemented the cockpit as a Web application called *MoReCo*, from the keywords *Mo*vie *Re*storation *Co*ckpit. *MoReCo* is available in an online version at this Web address http://159.149.129.182/moreco [2] The application allows the user to upload up to two videos and then computes six charts: *ml, mL, MRC, HF, CLV*, and ΔE. If only one video is uploaded, the generated charts show only the data relative to that video; when two videos are uploaded, the generated charts show a comparison of the results using lines in different colors and patterns. All generated charts can be downloaded as PNG figures. *MoReCo* has been implemented using HTML5, Chart.js, PHP and Matlab R2018a, and is downloadable at the same Web address of its online version[3]

6. Conclusions and future works

In this paper we have proposed a cockpit computing basic measures to support experts decisions during restored film assessment. The idea is to use a cockpit as an alternative to a single value IQ metric, that establishes a level of the general status of the film under exam but that does not provide specific information about the many aspects that concur to form that status. Any method providing a single IQ measure, is considered by film editors and curators as a *black-box*, which hides the real causes of the final output. Indeed, such a measure releases global information hard to be interpreted. As a result, users wishing to modify the processed video would not be able to understand which frame characteristics should be changed.

The application of the cockpit on restoration examples shows its characteristic and usefulness. The *MoReCo* cockpit is a preliminary implementation. The Web application allows to download the generated charts as PNG figures; however, in future versions, it will be extended to allow users to store the results for later uses.

Since the MoReCo web applications allows expert to send their own proposals, our future works will be devoted to expand the cockpit by inserting more quality related measures suggested by experts themselves, eventually clustering those with a similar meaning. Maybe this could foster new open databases to test new sets of shared quality assessment measures.

[2] Access credentials will be provided upon request to the corresponding author.

[3] The current implementation of *MoReCo* can be extended with other features. Suggestions, comments, requests, and proposals can be sent via the *MoReCo* application itself.

Declaration of Competing Interest

The authors declare no conflict of interest.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.patrec.2020.01.009.

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