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Spatio-temporal colour correction
of strongly degraded movies

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ABSTRACT

The archives of motion pictures represent an important part of precious cultural heritage. Unfortunately, these cinematography collections are vulnerable to different distortions such as colour fading which is beyond the capability of photochemical restoration process. Spatial colour algorithms—Retinex and ACE provide helpful tool in restoring strongly degraded colour films but, there are some challenges associated with these algorithms. We present an automatic colour correction technique for digital colour restoration of strongly degraded movie material. The method is based upon the existing STRESS algorithm. In order to cope with the problem of highly correlated colour channels, we implemented a preprocessing step in which saturation enhancement is performed in a PCA space. Spatial colour algorithms tend to emphasize all details in the images, including dust and scratches. Surprisingly, we found that the presence of these defects does not affect the behaviour of the colour correction algorithm. Although the STRESS algorithm is already in itself more efficient than traditional spatial colour algorithms, it is still computationally expensive. To speed it up further, we went beyond the spatial domain of the frames and extended the algorithm to the temporal domain. This way, we were able to achieve an 80 percent reduction of the computational time compared to processing every single frame individually. We performed two user experiments and found that the visual quality of the resulting frames was significantly better than with existing methods. Thus, our method outperforms the existing ones in terms of both visual quality and computational efficiency.

Keywords: Automatic colour correction, colour constancy, digital film restoration, dust & scratches, image enhancement, spatial colour algorithms.

1. INTRODUCTION

Colour films are most vulnerable to the degradation process. Photographic films contain not only dyes but also a few other components (sensitizers, colour couplers, stabilizers etc.) which can alter with time. Since the 1950s, colour film became the standard on which millions of cinematographic works were recorded. A couple of decades later, it turned out that this process was chemically unstable, causing the fading of whole film stocks with time. Usually, a bleached colour release print is the only available record of a film. Since the bleaching phenomenon is irreversible, photochemical restoration of bleached film is not possible, hence the incontestability of digital colour restoration.

Generally, movie restoration process can be pursued in two ways–photochemical and digital restoration process. Since each individual film reel is different from each other, they are analyzed and evaluated individually for different types of degradations. Many of the degradation factors like lacquering damage, emulsion separation, can be taken care of by means of chemical process or by applying chemical substrate. Fire damage, water damage etc are also possible to recover by photochemical process. But, many of these damages, like the fading phenomenon, cannot be removed by photochemical process only. They need further processing which is not photochemical, but it is digital restoration.

In digital movie restoration system, the first step is the scanning of the film negatives.[1] After the scanning is complete, the film can be considered as a digital representation of the film. Now, this digital representation goes through a number of processes to take care of the degradation factors like dirt/dust removal, scratch line

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removal, colour correction etc on the basis of image frequency analysis, motion analysis of pictures, and so on. And finally, in order to play the film in movie format, all restored images can be recorded back on movie films by using film recorder.[2]

Digital movie restoration is comparatively a new area of research in the field of colour image processing. In case of colour correction process, several spatial colour algorithms (SCA) can be considered. Among them, Retinex, ACE etc are used by many researchers and STRESS[3] is a new addition to this family of algorithms. But, there has always been the problem of long computational time with the models like Retinex and ACE; besides this, these techniques are not totally unsupervised. Sometimes, expertise of users have been taken under consideration to decide the best colour for some specific zones like sky, ground etc and then the rest of the algorithm have been processed on the basis of that zone colour selection assumption.[4] Hence, there are some key places which needs to be taken care of while considering the implementation of movie restoration process.

An important issue in colour correction is the enhancement of the colour information in a balanced way in all the channels. This enhancement should be applied before the degraded image is processed by colour enhance models, STRESS or ACE etc. This enhancement should be able to remove most of the the strong colour cast of the old films. Another important factor is, the preservation of the mean chromatic, saturation and lightness value of the channels of the images after they are processed by the colour image enhancement models, STRESS or ACE etc. When images are processed by these models, the processed images loose the mean saturation, lightness etc value, which are important to preserve for natural outlook from the HVS perspective. So, some postprocessing mechanism must be applied to preserve these basic properties of the image. Apart from this, old degraded films often contain scratch lines. This problem is often treated independently of colour correction in movie restoration. However, in the case of SCAs, the two problems are not fully decoupled since the scratch lines also change the local colour context. Moreover, the issue of computational time is another big factor in movie restoration. A movie consists of large number of frames. So, the restoration method must have to be computationally efficient. Besides this, would it be possible to develop a system which is free of user intervention, is also an open question of research in movie restoration area.

In this paper, we have put an effort to answer these questions and offered some solutions by which we would hopefully be able to solve these particular existing problems in old movie restoration. Our work follows the no-reference strategy, since the colour films are already degraded and there is no good quality copy of the degraded film to compare the result.

In order to automate the total process of colour restoration, we have proposed the following idea which contains the following major steps. Firstly, we have proposed a preprocessing technique for enhancing the colour information in all the channels in a balanced way. The output image from this preprocessing technique is then processed by the STRESS algorithm so the computational time is reduced at a certain level. Since, STRESS uses an extremely small number of sample points and implemented using two envelopes to characterize the local visual context, the computational time is expected to be reduced significantly. The properties of STRESS are in line with other SCA.[5] Secondly, we suggested and implemented a postprocessing mechanism[6] for preserving the lightness and saturation of the preprocessed image which would be further processed by the STRESS model.

Moreover, we have tested existing algorithm to remove the scratch line from the degraded films. We chose one of the existing algorithms and applied to the degraded films before the preprocessing step. The reason, we applied the scratch removal process before the preprocessing step, is that, while enhancing the saturation, the scratch lines will also be enhanced and they will eventually degrade the total quality of the image. We have also analyzed the effect of this scratch removal on colour restoration. When we tested our algorithm on the same material with and without the defects, surprisingly, we found that the presence of the defects only very weakly influences the performance of the colour correction algorithm for the material we tested.

Besides this, we have suggested and implemented an efficient temporal domain method, by which we, hopefully, will be able to reduce the computational time for the next sequence of frames comparing with the first frame in a single cut of a movie. All the methods are free of user intervention. There are few parameters in the postprocessing step which needs to be tuned depending on the image. These steps are depicted in Fig. 1. In the following sections, we have discussed each of these steps more details.
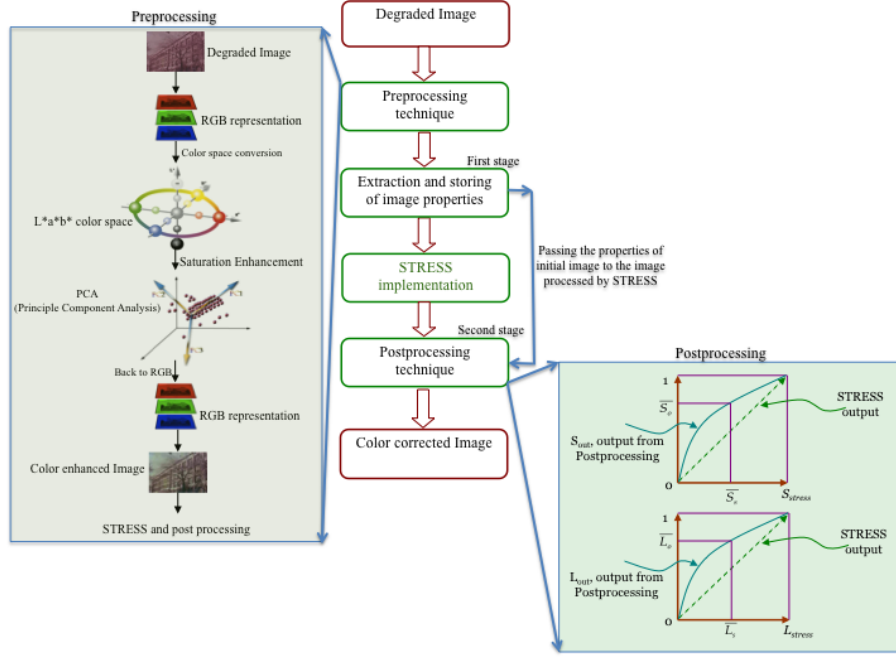
Figure 1. Basic workflow of our idea.

The rest part of the paper is arranged like following: Section 2 describes some existing movie restoration methods and the STRESS model, in Section 3 our proposed method has been described, Section 4 shows and describes the results associated with our ideas and finally, in Section 5 we have drawn our conclusion.

2. BACKGROUND

In the next two subsections, we will discuss about different degradation factors and solutions provided by different researchers and about one particular algorithm, STRESS, which we have used in our work.

2.1 Digital Movie Restoration

While going through the existing works done, related to movie restoration of old motion pictures, so far, we found out that this task has been accomplished in different manners. Some tasks have been pursued in the chemical phase while some others discuss about colour correction in the digital phase. In the digital phase, in case of colour correction process, several SCAs like Retinex, ACE, STRESS etc have been used by many researchers. Retinex,[7] developed by Land and McCann, is one of the earliest models that works with locality of perception. A number of implementations and analysis have been carried out based on this first model. Further developments [8,9] of this model mainly differed in the technique of attaining locality. Random Spray Retinex (RSR)[10] is a recent implementation which investigates the effect of different spatial samplings by replacing paths with random sprays i.e. two dimensional point distribution across the image. ACE (Automatic colour equalization), developed by Rizzi et al.,[11] is another technique to keep the local and global effect of digital images, accounting for chromatic/spatial adjustment and maximizing the image dynamic. ACE showed potential results to mimic several characteristics of the Human Visual System (HVS), like colour and lightness constancy, controlling the contrast etc. Though these algorithms provide good results, they suffer from long computational time, which has always been the weak point in this family of algorithms.[5] Another recent development in the field of image enhancement applications is STRESS (Spatio-Temporal Retinex-like Envelope with Stochastic Sampling) developed by Kolas et al.[3] It is implemented with an extremely small number of sample points, using two envelopes for characterizing the local visual context. STRESS shows promising result in mimicking different properties of the HVS like local contrast stretching, automatic colour correction, high dynamic range

image rendering etc. It has been successfully implemented for spatial gamut mapping and colour to gray scale conversion as well.

We found out that not much works have been done in this automatic processing phase of digital restoration of old movies. The existing works done so far are not so long ago. Arnaldo et al. proposed the approach[12] for old movie restoration in which, they proposed the solution by using an opening by temporal surface which is followed by a spatial geodesic reconstruction by dilation using structuring element, in order to find out the local defect detection problem and defects in consecutive images with any intersection. Guimaraes et al. also proposed a similar approach[13] of old movie restoration through using Opening by Surface. They proposed a method for restoring old movie using opening by surface which eliminates image information by area attribute, independent of the shape of its components.

Chambah et al. proposed a two stage colour correction algorithm[4] in which firstly the degraded images are non-uniformly enhanced in saturation level and then they applied the well-known Gray World[14] and Retinex White Patch method[15] for the colour balance. Their approach consists of using a different method depending on the tone of the zone to correct. Another work[16] by Chambah et al. pursued the colour correction of faded films by means of applying a two stage method. Firstly, they enhanced the saturation level and then they applied ACE algorithm[11] for further colour correction. Their approach involves some sort of user supervision and also the major drawback is the large computational time. They offered a local LUT based ACE algorithm, but the resulting image were not as reliable as the original ACE.

Another comparatively new approach[17] for digital movie restoration is suggested by Rizzi et al., in which they divided the movie into different shots and then implemented the ACE algorithm[11] for colour correction. Their result seems satisfactory to a certain level, but again it suffers from long computational time. The concept of using rational function filters have been performed in old movie restoration by Khriji et al.,[18] in which they proposed a spatial rational interpolator scheme for reconstructing the missing data, after the stationary and random defects have been localized. They focused on the blockiness and jaggedness degradation. Though the random defect removal performs at a satisfactory level, but stationary defect removal method suffers from high computational complexity.

Recently, a fusion based approach[19] have been proposed by Maddalena et al. for digital movie restoration. They proposed a new digital scratch restoration algorithm which achieves accuracy results higher than that of already existing algorithms and naturally adapts for implementation into high-performance computing environments. Their intention was to adopt several relatively well-settled algorithms for the problem at hand and combine obtained results through suitable image fusion techniques, with the aim of taking advantage of the adopted algorithms' capabilities and, at the same time, limiting their deficiencies.

The above discussion is a brief follow-up that covers the colour degradation factors of old movie films and their possible solutions by different researchers. In our paer, we mainly focused on the colour reconstruction factor. We suggested a method which automates the process of colour restoration in old movie films. We have used the STRESS algorithm as an image enhancement model. In the next section, we have discussed briefly about STRESS algorithm.

2.2 The STRESS Algorithm

We have used the STRESS model for the purpose of image quality enhancement. The reason behind choosing the STRESS model is: STRESS is comparatively faster and efficient and it preserves the basic shape of the colour histograms in each channels. STRESS outperforms some of the existing algorithms like ACE in case of computational time. So, the choice of STRESS as image quality enhancement model was solely for the speed of computation and nice quality image.

STRESS is an image quality enhancement technique which is implemented with an extremely small number of sample points, using two envelopes to characterize the local visual context. The central part of the STRESS algorithm is to calculate, for each pixel, the local reference lighter and darker points in each chromatic channel. This is done through calculating two envelope functions, the maximum and minimum envelopes, containing the image signal. The envelopes are slowly varying functions, such that the image signal is always in between the envelopes or equal to one of them.[3]
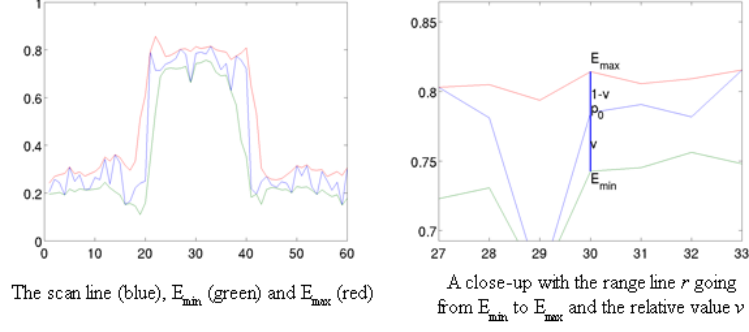
The scan line (blue), E_{min} (green) and E_{max} (red)

A close-up with the range line r going from E_{min} to E_{max} and the relative value v

Figure 2. Illustration of the envelopes of one scan line of an image.

For each pixel, p_0, the maximum and minimum envelopes, E_{max} and E_{min} are computed in an iterative manner using N_i iterations. In every iteration, N_s pixels p_i, $i \in \{1, ..., N_s\}$ are sampled at random with a probability of $1/d$, d being the Euclidean distance in the image from the sampled pixel to the pixel in question. An illustration, taken from [3], of the envelopes for one scan line of an image is shown in Fig. 2.

The range r of the samples, the relative value v of the center pixel, $\bar{v}$, $\bar{r}$, E_{min} and E_{max} are calculated from the following equations taken from [3].

$$S_{max} = \max_{i \in \{0,...,N_s\}} p_i, \quad S_{min} = \min_{i \in \{0,...,N_s\}} p_i, \quad r = S_{max} - S_{min} \tag{1}$$

$$v = \begin{cases} 1/2, & \text{if } r = 0 \\ (p_0 - S_{min})/r, & \text{otherwise} \end{cases} \tag{2}$$

$$\bar{r} = \frac{1}{N_i} \sum_{N_i} r \quad , \quad \bar{v} = \frac{1}{N_i} \sum_{N_i} v. \tag{3}$$

$$E_{min} = p_0 - \bar{v}\bar{r} \quad , \quad E_{max} = p_0 + (1 - \bar{v})\bar{r} = E_{min} + \bar{r} \tag{4}$$

The final STRESS value of a pixel, p_{stress}, is calculated by the following Eq. (5), which is further generalized by substituting E_{max} and E_{min} from Eq. (4) into Eq. (5). The final p_{stress} is calculated by Eq. (6).

$$p_{stress} = \frac{p_0 - E_{min}}{E_{max} - E_{min}}. \tag{5}$$

$$p_{stress} = \bar{v}. \tag{6}$$

This technique is applied for all the three channels in the colour image and finally, we get the desired enhancement in the colour of the image. We applied this technique for restoration of colour information for degraded films. From [3], we can also get a general idea about temporal domain STRESS implementation. In [3], they have suggested to use the running average, $\bar{r}$ and $\bar{v}$, in such a way that local reference black and white will not only depend on the current frame of the movie, but also on the previous frames as well. Since, $\bar{r}$ and $\bar{v}$ are computed in an iterative approach, performing the iteration over the consecutive frame sequences would provide a better and faster solution for motion pictures. The equations they suggested for this iterative approach are:

$$\bar{r} = \alpha r + (1 - \alpha)\bar{r}_p \tag{7}$$

$$\bar{v} = \alpha v + (1 - \alpha)\bar{v}_p \tag{8}$$

Here, $\bar{r}_p$ and $\bar{v}_p$ are the values of $\bar{r}$ and $\bar{v}$ in the previous iteration respectively. The choice of the parameter, α and the number of iteration on each frame will eventually affect how quickly the local reference black and white will change in the image.

In this paper, we have also implemented temporal domain processing, but in a different manner. We will discuss about that in later section.

As we will move forward to dig more deeper into our study and discuss different aspects of our implemented methods, we will find out that the processes we offered here are very efficient and faster than the existing techniques. Moreover, our method provides very good result from the HVS perspective and from the statistical point of view as well.

3. PROPOSED METHODS

3.1 Preprosessing: Colour Balancing

We have described this process of colour balancing as the preprocessing step in our suggested method. Colour balancing process involves enhancing the colour information in the channels which have less colour information. In case of degraded images, almost all the colour information reside in a single channel, other channels possess very few colour information. Because of this imbalance in distributing colour information among the three channels, colour cast is found in the degraded images. We have applied some techniques to remove this colour cast to a certain level.

For enhancing the colour information, at first we transformed the colour space of the image from RGB to CIELAB. We have chosen the CIELAB space because it is more uniform and we can control the lightness and chromaticity parameters individually, independently and efficiently. After implementing the conversion, we get the corresponding L*a*b* values from the original degraded RGB image.

We used principal component analysis (PCA) to de-correlate the data among different channels. So, if we apply PCA to the image which is in CIELAB colour space, then, the colour information will be divided into three different principle components (PCs). For enhancing the colour information from this kind of degraded films, we designed the working flow as the left part of the block diagram in Fig. 1. From this block diagram, it is clear that at the very first stage, we work with the RGB image which is a strongly degraded frame from a movie. Then, we convert the colour space to L*a*b*. The later step is the balancing of colour i.e. enhancing the saturation.

For saturation enhancement, we have used PCA change the basis. We did not change the lightness information i.e the L* channel information of the image in the CIELAB colour space and worked with the other two dimensions, a* and b*. We implemented the following steps in PCA to enhance the colour information.

Let us consider, I_d as the independent colour channel axis. We calculated a parameter, m in Eq. (9), which is the ratio of the squared root of the eigen values, d_1 and d_2.

$$m = \sqrt{d_1}/\sqrt{d_2}. \tag{9}$$

Then, we calculated the first, Eq. (10) and the second, Eq. (11) independent axis as follows:

$$I'_{d1} = I_{d1} \times 2x \tag{10}$$

$$I'_{d2} = I_{d2} \times m^x. \tag{11}$$

Since, we intend to enhance the second independent axis more than the first independent axis, we have multiplied the first independent axis with a factor of 2x and the second independent axis with m^x. Here, $m^x > 2x$, since $m \geq 2.5$ and our highest estimation of x is 0.65. In this way, colour information is enhanced in a balanced way along both the axes. After enhancing the colour information in the CIELAB space, the colour enhanced image is brought back again to the RGB space for further processing.
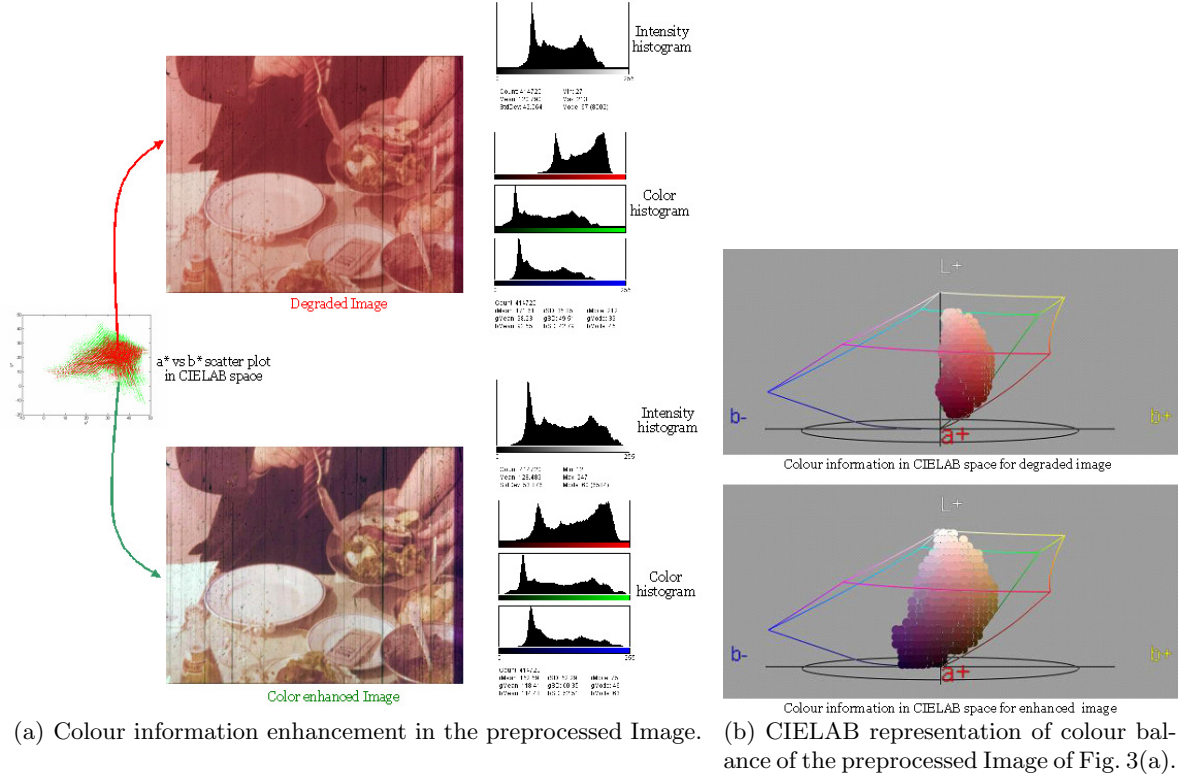
(a) Colour information enhancement in the preprocessed Image. (b) CIELAB representation of colour balance of the preprocessed Image of Fig. 3(a).

Figure 3. Enhancement of colour information in the preprocessed Image.

Value of x is gained from a trial and error basis. We defined 5 different saturation parameters, $x = \{0.35, 0.45, 0.5, 0.60, 0.65\}$ and picked the one which the observers liked most. For picking up the most chosen value of x, we arranged a psychophysical experiment which will be discussed later in section 4. The following Fig. 3 shows the enhancement of colour with the parameter which the observers liked most, i.e. with $x = 0.5$.

From Fig. 3, we can observe that both the intensity histogram and the colour histograms of the colour enhanced image cover more dynamic range than the degraded image. Moreover, the a^* versus b^* scatter plot in Fig. 3 also shows the amount of enhancement in the CIELAB space. In the scatter plot, the red area indicates the amount of colour information in the degraded image, whereas the green area indicates the amount of colour information in the colour enhanced image. The enhancements of colour information for Fig. 3(a) is presented in Fig. 3(b) in the CIELAB colour space.

Considering the depicted resulting images, we can comment that the preprocessing method efficiently balances the color information in all the channels of the image. The resulting image have very less colour cast and the colour of different objects are much more prominent than the degraded image.

3.2 Postprocessing: Spatial Domain

The original degraded images contain strong colour cast, which is also known as the fading effect. The resulting images from the preprocessing technique have very less colour cast comparing with the original degraded image. Now, the colour information of these resulting images should be restored, since this is the focus of our work. In order to restore the colour information, we applied STRESS algorithm.[3] We also applied our postprocessing technique[6] to the resulting images from STRESS algorithm. This postprocessing is applied mainly to preserve the lightness and saturation level of the preprocessed images in the final output images from STRESS algorithm.

The working process of colour restoration consists of three main steps. The first two steps, the preprocessing technique and the STRESS algorithm have been discussed already in previous sections. Here, we will discuss about the working criteria of our postprocessing technique.

Like any other image enhancement models, when STRESS is applied to an image, the output that is produced, doesn't preserve the basic properties like mean chromatic channel value, mean lightness or mean saturation etc.[6] So, the images produced from STRESS algorithm, seem to be over saturated and of low lightness level comparing to the preprocessed image. Hence, we applied our postprocessing technique[6] to preserve the mean lightness and mean saturation level of the preprocessed image and pass it to the image after STRESS is implemented. The workflow of this stage is depicted in the middle part of Fig. 1.

From Fig. 1, we can see that, in the first stage, properties of images like mean lightness and mean saturation are extracted and stored. After that, the image is processed with STRESS algorithm. After implementation of STRESS, in the second stage, the resulting image is further processed with the properties stored in the first stage. The resulting image is the final image with colour correction. For postprocessing the image from STRESS, we used the KMG (Keep Mean by Gamma)[6] technique for preserving the mean lightness and saturation for the final output image. For extracting the saturation and lightness value, we converted the RGB colour values to HSL and then extracted and stored the values of saturation and lightness. We did not consider hue for this postprocessing. After extraction of values, we again convert back to RGB and implement the STRESS algorithm. Then, we convert RGB values of the image from STRESS model to HSL values and applied the KMG postprocessing technique and finally, image is converted back to RGB space.

The postprocessing method, KMG, is illustrated in the right part of the diagram in Fig. 1. In the right part of Fig. 1, in the upper diagram, $\bar{S}_o$ and $\bar{S}_s$ indicate the mean value of saturation channel of the initial image and of the image from STRESS algorithm respectively. The upper diagram shows the final value, S_{out}, for saturation channel, after processing the saturation channel value, S_{stress}, from STRESS algorithm. S_{out} can be obtained by the following equation, modified form, taken from [6]:

$$S_{out} = S_{stress}^{\gamma^S}; \quad \gamma^S = \frac{\ln \bar{S}_o}{\ln \bar{S}_s} \tag{12}$$

The lightness value, L_{out} can also be derived in the same process as L_{out} by the following equations:

$$L_{out} = L_{stress}^{\gamma^L}; \quad \gamma^L = \frac{\ln \bar{L}_o}{\ln \bar{L}_s} \tag{13}$$

The resulting colour corrected image is depicted in Fig. 4(a) and Fig. 4(b).

In Fig. 4(a) and Fig. 4(b), we can observe that the image on the upper right position has some kind of burning effect, it seems that this image is over saturated. Besides this, it looks a bit darker than the preprocessed image (lower left position).The reason behind this is the image enhancement model, STRESS. We know that after processing by STRESS, some basic properties of the image are lost in the final resulting image.[6] So, in order to maintain those basic properties like the saturation level and the lightness level, we implemented our postprocessing technique and finally, in the resulting image, we can observe the colour corrected image with expected saturation and lightness level. We can figure out this effect by looking at the intensity and colour histograms of the images on upper right and lower right position. Here, the upper right image is the image produced by only implementing STRESS on the preprocessed image.

3.3 Temporal Computation and Postprocssing

Till this part of our work, we have been dealing with the spatial domain implementation of our method with STRESS and postprocessing. We were implementing our method on each frames. But, in a movie, we have large number of frames. There are a number of shots, cuts etc in a movie. In each cut, there are a number of frames. So, for correcting the colour of the whole movie, each of those frames should be considered. We have suggested a temporal domain method which works on the frames in a cut. Our method performed quite well and was able

(a) Effect of postprocessing on the STRESS image-1.   (b) Effect of postprocessing on the STRESS image-2.
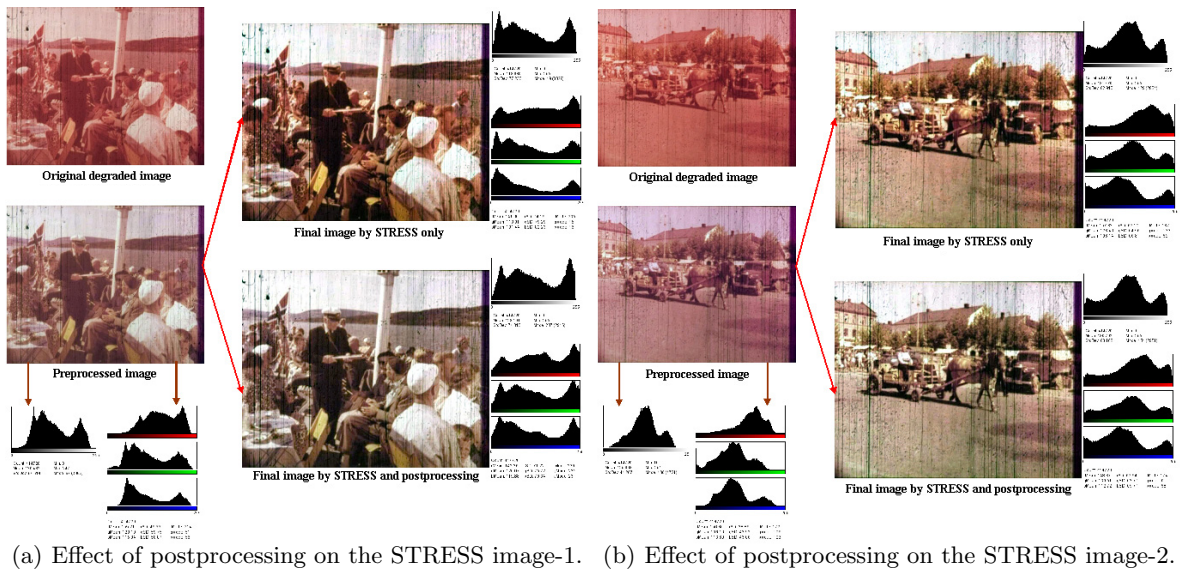
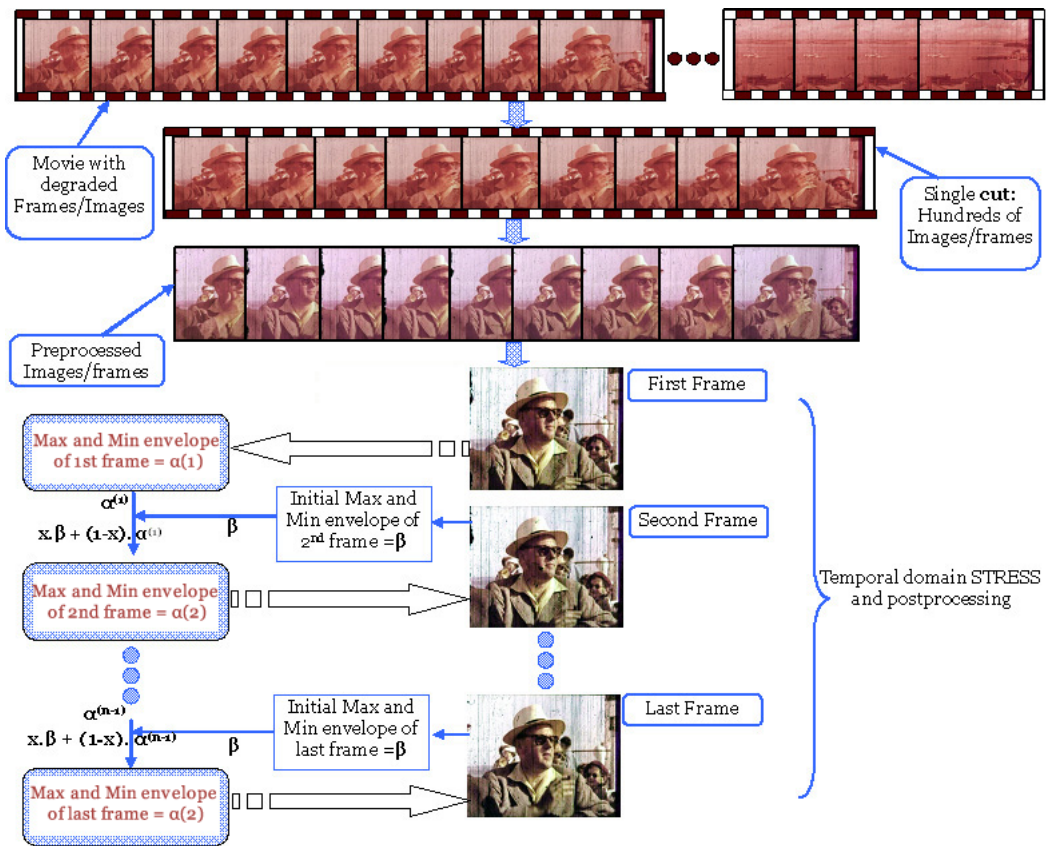Figure 4. Effect of postprocessing on the STRESS images.

Figure 5. Workflow of the implementation of the temporal domain method.

to gain 80% reduction of computational time in the consecutive frames, comparing with the first frame in a cut. For temporal domain implementation we followed the following workflow depicted in Fig. 5.

In Figure 5, x is the weight factor. From Figure 5, we can observe that, we worked on degraded old film(topmost image). From this film, we worked on each cut (second image from top) in the movie. The cut might contain quite a number of frames and the background objects in a cut doesn't change very much. For the frames in a cut, we applied our preprocessing method (third image from top) for enhancing the colour information. Then, we applied our temporal domain STRESS and postprocessing method on the frames of a cut. In 3, the final STRESS value, p_{stress} was calculated by using Eq. (6). Here, for temporal domain method, we stepped back from Eq. (6) and used Eq. (5) for calculating p_{stress} value. Now, for calculating the minimum and maximum envelopes for each pixels in each channels, we followed an efficient strategy to reduce the computational time at a very low level.

For the first frame of the cut, we applied our method and calculated the minimum and maximum envelopes for each pixels in each channels and then we stored these envelopes in global variables for using them for the next frame. For the next frame, we firstly calculated it's own minimum and maximum envelopes for each pixels in each channels. Then, the minimum and maximum envelopes of the first frame are associated with the minimum and maximum envelopes of the current frame. We defined a weight factor for deciding how much information from the previous frame should be associated with the current frame. The following set of equations were used for calculating the envelopes and pixel value, p_{stress}.

$$G^n_{min} = \alpha E^n_{min} + (1 - \alpha)G^{n-1}_{min} \tag{14}$$

$$G^n_{max} = \alpha E^n_{max} + (1 - \alpha)G^{n-1}_{max} \tag{15}$$

$$p_{stress} = \frac{p_0 - G_{min}}{G_{max} - G_{min}} \tag{16}$$

Here, G^n_{min} and G^n_{max} are the final envelopes of the nth frame and α is the weight factor.

From Eq. (14) and Eq. (15), we can see that, for calculating the final envelopes of the current frame, the initial own envelopes are multiplied with the weight factor, α and then it is added to the envelopes of the previous frame, G^{n-1}_{min} and G^{n-1}_{max}, with a multiplicative coefficient of $(1 - \alpha)$. After calculating the p_{stress} value for each pixel in each channel, we store the envelopes of the second frame for using them in third frame and so on.

Now, in this strategy, we save a lot of computational time. Because, we apply our method with a high number of iteration only for the first frame for getting a noise free resulting image. For the next frame, we run our method for very few iterations. Usually, with a very few iteration, the resulting image should be very noisy. But, since, we are associating the envelopes of the previous first frame, which is noise free, we get a better image similar to the resulting image of the first frame.

We know that the envelopes are considered as the local reference maximum and minimum points. So, while calculating the envelopes of a particular point, the most nearby parts of the image influence strongly on the calculation. Hence, when we associate the envelopes of the previous frame with the current frame, the current frame gets the features of the envelopes of the previous frame. How much information of the previous frame will be associated is decided by the weight factor, α. For extreme case, for weight factor of 0, we use no information of envelope from the current frame and use all the information of envelope from the previous frame; hence the iteration needed for the current frame is $\equiv 0$. Similarly, for weight factor of 1, we use no information of envelope from the previous frame and use all the information of envelope from the current frame; henc,e the iteration needed for the current frame is equivalent to the iterations needed for the first frame and so on. If we use weight factor of 0, then some effect like, afterimage or trailing effect, might appear in the current frame. Since, in case of 0 weight factor, we use all the information of envelopes from the previous frame, for a rapid motion on the foreground image of the previous frame might appear as an afterimage or like a shadow trail in the current frame. So, for avoiding this kind of effect, we need to set the weight factor to a certain level. We have depicted the implementation result of our method and the effect of using extreme weight factor of 0 in the next section.
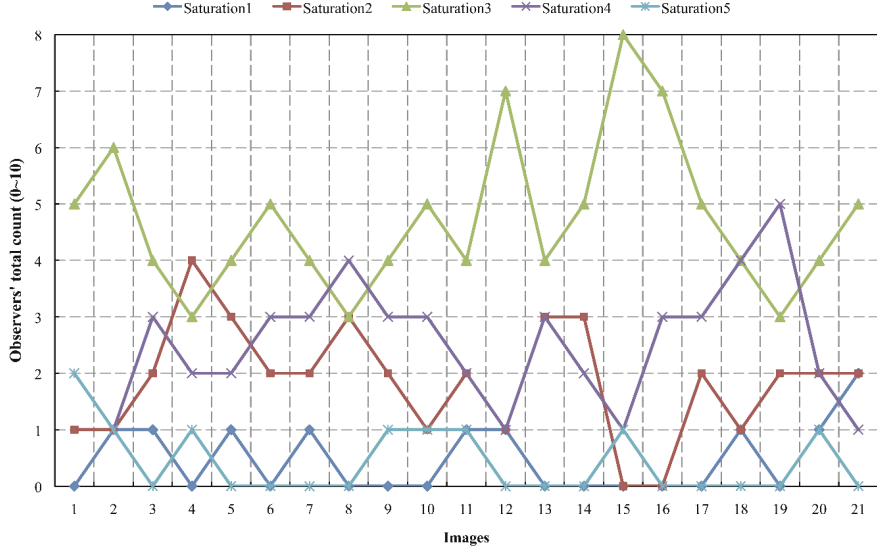
Figure 6. Statistical analysis of the psychophysical experiment for the images.

4. RESULTS AND DISCUSSION

4.1 User Test for Preprocessing

For picking the most preferable value of the saturation parameter, x in Eq. (10) and Eq. (11), we arranged a psychophysical experiment. In that experiment, we asked the observers to select the most preferable image for him/herself from 5 variations of saturation of the same image. We got 210 observation results from 21 images and 10 observers. We used statistical analysis method to analyze the results from the psychophysical experiment. The null hypothesis for the saturation level 3, Fig. 6, is "The observer finds all the five variations of images similar and they can select any one of the five images with equal probability".

The Significance level is 0.05 i.e. 5%. From the experiment, we got 21 P values for 21 Images. We used double sided calculation of binomial distribution. We used the formula, $P = 1 - CDF(x, n, p)$, for calculating P values where CDF is the cumulative distribution function of the binomial distribution. If we calculate the P value at a time for all the images and for all the observers for Saturation Level 3 we get $P = 0$ which is less that the significance level 0.05. Here, x=99, n=210 and p=0.2. So, we can reject the null hypothesis and can conclude that the outcome we have observed is improbable due to chance.

We used the preprocessing method to reduce the colour cast by enhancing the colour information of the channels. The resulting image, Fig. 3, shows the performance of this method. The performance can also be measured from the intensity histograms and scatterplot.

4.2 User Test for Postprocessing

We arranged a psychophysical experiment to compare our final output image with an existing algorithm, ACE. After the preprocessing step, we implemented ACE algorithm and then compared the result obtained with STRESS implementation. We had total 210 observations from 21 images and 10 observers. The observers, being unaware of specific algorithm for specific images, were asked to select one image from two different outputs from the two methods of the same image. We analyzed the results from the experiment by statistical method. The null hypothesis for the experiment is "The observer finds both the images from ACE and STRESS equal and they can select any one of them with equal probability". The Significance level is 0.05 i.e. 5%. We had 21 P values which is depicted in Figure 7.

We used double sided calculation of binomial distribution. We used the formula, $P = 2 \times CDF(x, n, p)$, for calculating P values. If we calculate the P value at a time for all the images and for all the observers for
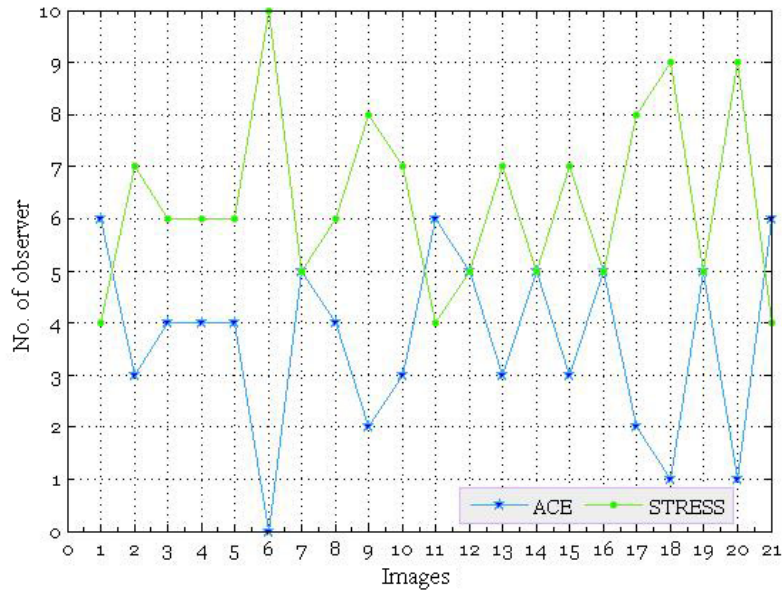
Figure 7. Statistical analysis of the psychophysical experiment for ACE vs STRESS.

Saturation Level 3 we get $P = 0.001356$ which is less that the significance level 0.05. Here, x=77, n=210 and p=0.5. So, we can reject the null hypothesis and can conclude that the outcome we have observed is improbable due to chance.

We used STRESS and postprocessing algorithm for restoring the colour information. The image quality is improved by applying the postprocessing and STRESS method comparing with the ACE method, which is depicted in Figure 8 as well.

In Figure 8, in addition to the cut off of the red channel in colour histogram with the ACE, in the intensity histogram, a drop off of the intensity in the upper region(marked by red rectangle) is also found. As a result, the final image have some darkening effect in some areas in the image. Besides this, our method with postprocessing and STRESS outperforms the ACE in case of computational time as well. For an image of dimension 720×576, porstprocessing and STRESS take 31 seconds, whereas, ACE takes 15509 seconds. Even ACE with Local Linear Lookup table (LLL) methods takes 51 secods, whereas, STRESS takes 31 seconds. STRESS with LLL would have performed far better than ACE with LLL if tested.

So, after considering all the quality judgment factor, we can state that, out method with STRESS performs quite good in comparing with the existing methods like ACE: in case of enhancement quality, computational time and statistical result from psychophysical experiment.

4.3 Computational Time versus After-image Effect

While implementing the temporal domain method, we came across the after image effect. If we set the weight factor very low (close to 0), for example 0 or 0.1 or 0.2, then, we can see the after image effect on the current frame. In case of after image effect, some shadow part of the previous frame appears in the current frame. For example, if a person moves his hand from one place to another, then, in the first frame the hand will be in one place and in the next frame, the hand will be in another position. So, if we process these two frames, then, the position of the hand in the first frame will appear at the same position in the second frame in a smoky way; a trail of the hand movement will be shown. This effect is depicted in Figure 9(a).

The reason behind this after image effect is the usage of less information of envelopes(weight factor is close to 0) from the current frame and more information of envelopes from the previous frame. If we increase the weight
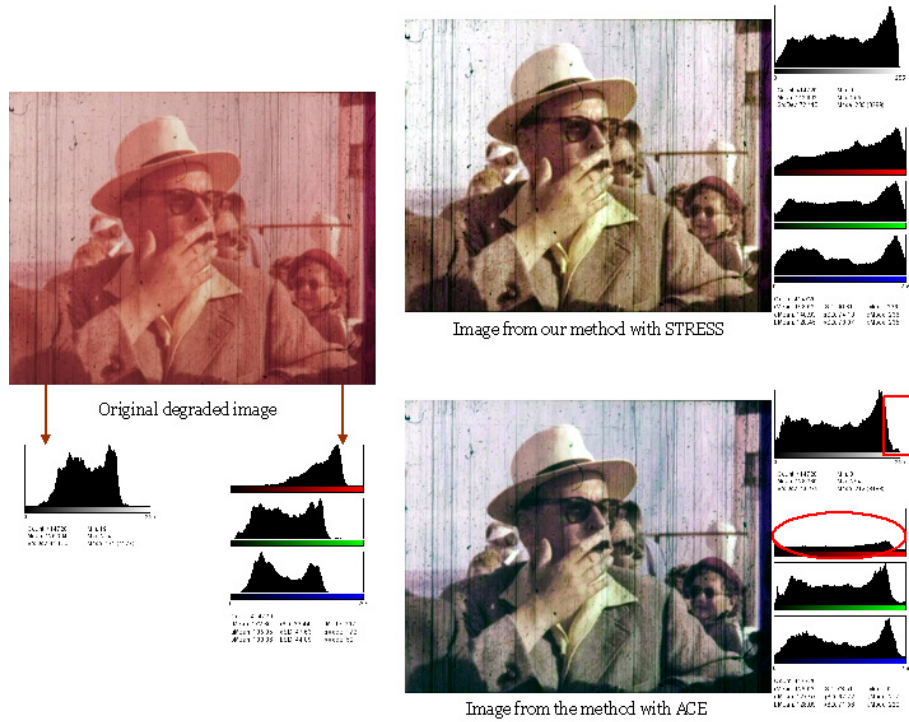
Figure 8. Resulting images from the method with ACE and with STRESS.

(a) After image effect on video frame.

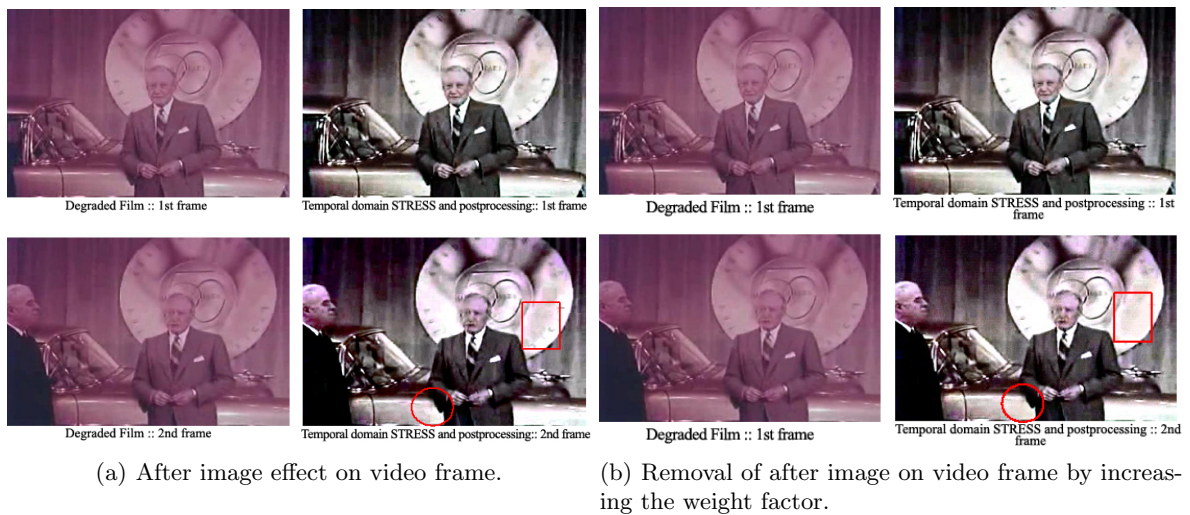(b) Removal of after image on video frame by increasing the weight factor.

Figure 9. Effect of postprocessing on the STRESS images.

factor, for example weight factor, $\alpha = 0.7$, then we do not see any after image effect on the current frame. Since, we have started to use more information from the current frame and less information from the previous frame, the effect of the envelopes of the previous frame is reduced and hence, the after image effect is also disappeared. We can observe the removal of after image effect by selecting the weight factor, $\alpha = 0.7$ in Figure 9(b). We can observe in Figure 9(b), which contains the exact frames as in Figure 9(a), that, the after image effect is now removed from the second frame. So, by increasing the weight factor, we can remove the after image effect in the video frames.

But, the issue here is that this increase of weight factor also increases the computational time. But still, the second frame's computational time is reduced by more than 80% comparing to the first frame. Because, if we have weight factor close to 0, then, only 1 or 2 iteration is enough for getting the similar quality of the image as the first frame. Since, we have increased the weight factor to 0.7 for removing the after image effect, the required iteration for second frame is only 15 (while for the first frame it is 90), hence the computational time for second frame is reduced by more than 80%.

5. CONCLUSION AND FUTURE WORK

We have proposed here an automatic colour correction technique which eventually automates the colour fading restoration process. We tried to solve some basic problems that exist in colour restoration process. Firstly, we have proposed a preprocessing method which helps to reduce the strong colour cast of the old movie to a very low level. Besides this, we have offered a very effective postprocessing technique for preserving the mean lightness and the saturation level of the preprocessed image after they are processed by the colour enhancing models like ACE or STRESS. We have also analyzed the effect of scratch line on old movies by implementing one existing technique to remove the scratch lines.

Apart from this, we have proposed a temporal domain postprocessing method which reduces the computational time in processing the large number of movie frames. We were able to significantly reduce (more than 80% reduction) the processing time for the consecutive frames in the cut of a movie. Besides this, we have performed a psychophysical experiment for the preprocessing phase and we have also performed another psychophysical experiment for comparing the resulting image from our method and the method with ACE. The experiment was totally bias free and the result obtained was quite satisfactory. Hence, we can comment that our method produces resulting images which are pleasant from the perspective of the HVS, the processing time is very fast in comparing with the existing methods and the colour information in all the channels are well balanced after performing the method.

In future, several strategies could be taken for speeding up the total processing even more; like implementation of Local Linear Lookup Table (LLL) method STRESS, visual saliency for enhancing the specific part of a frame rather than the whole image, motion estimation and detection for enhancing the particular area where the change in motion occurs in a frame. This would certainly save a lot of computational time.

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