A Review of Redeye Detection and Removal in Digital Images Through Patents

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Abstract: Many image processing software applications in the market offer redeye removal solutions. Most of these methods have been patented mainly by big companies. In this paper we summarize the history and the state of the art of redeye detection and correction in digital photography, starting from the analysis of these patents. We describe the main approaches with the help of flowcharts and figures, with special emphasis on how to evaluate the whole process of detection and correction with respect to the final results and what the user would like to obtain.

Keywords: Redeye removal, Redeye detection, Redeye correction.

INTRODUCTION

The redeye effect is a well known problem in photography. It is often seen in amateur shots taken with a built-in flash, but the problem is also well known to professional photographers. Redeye is the red reflection of the blood vessels in the retina caused when a strong and sudden light strikes the eye. Today's compact cameras exacerbate the problem because of the proximity of the flash unit and the lens. A common technique to reduce redeye is to adopt multiple flashes to contract the pupils before the final shot. However, this way the effect can only be reduced and not completely removed. In addition, a flash consumes a significant amount of power.

Fixing redeye artifacts digitally has become an important skill with the advent of digital technologies, which permits to acquire digitalized images either directly with a digital camera or converting traditional photos with scanners. Also the widespread use of small devices with built-in flashes, including cell phones and handheld computers, produces a large amount of digital photographs that are potentially redeye affected.

Fixing the redeye defects is a particularly severe issue, especially in a completely automatic way as can be understood considering Fig. (**1**), where images affected by different kinds of redeye defects are shown. First of all, the color distribution of the red eyes is significantly spread, whatever the color space is considered. Moreover, it overlaps the skin tone color distribution. The detection of eyes could also be difficult due to presence of possible occlusions (for instance glasses, hair, etc. as shown in Fig. (**1b &1c**). Another aspect to be considered is that sometimes only one eye is red, Fig. (**1b** and **1d**), and thus in these cases we first have to detect a single red eye and then guarantee a correction that makes the color of the corrected eye similar to the other one.

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In this paper we present a review of detection and correction of redeye defects in digital images through the analysis of the main patents. The whole process is commonly divided into two separate modules: the detection of the redeye defects, and the correction of these artifacts. Thus, this paper also follows the same subdivision. After a preliminary chronological description of the main works available in the literature and of the related patents (Section 1), the detection strategies are firstly considered in Section 2. The analysis starts from a brief summary of the possible procedures (Section 2.1), and then analyzes in more detail the main redeye detection (Section 2.2) and redeye validation approaches (Section 2.3). In Section 3 the color correction strategies are reported, while in Section 4 an analysis of the possible different evaluations of the redeye detection and correction processes are presented. In this Section there are also presented recent works that based the correction step on the analysis of the results of the redeye detection phase.

Finally in the conclusion we present our considerations about the state of the art of redeye detection and correction, with particular emphasis on what is almost solved and on the open issues that still need to be considered.

CHRONOLOGICAL REVIEW

Currently, many image processing software applications in the market offer redeye removal solutions. Most of them are semi-automatic or manual solutions. The user has to either click on the redeye or draw a box containing the redeye before the redeye removal algorithm can find the redeye pixels and correct them. Also several big companies, such as Hewlett Packard, Kodak, Fuji, Agfa, Nikon, and others have developed completely automatic tools. A typical problem with most of these algorithms is poor segmentation. Even with user input, these algorithms sometimes identify redeye pixels too aggressively, darkening eye lid areas, or too conservatively, leaving many redeye pixels uncorrected.

Another aspect is the low efficiency of several methods; in fact, to avoid erroneous corrections of non redeye pixels, it is preferable to reduce the overall efficiency instead of creating a huge number of new defects. As a typical example

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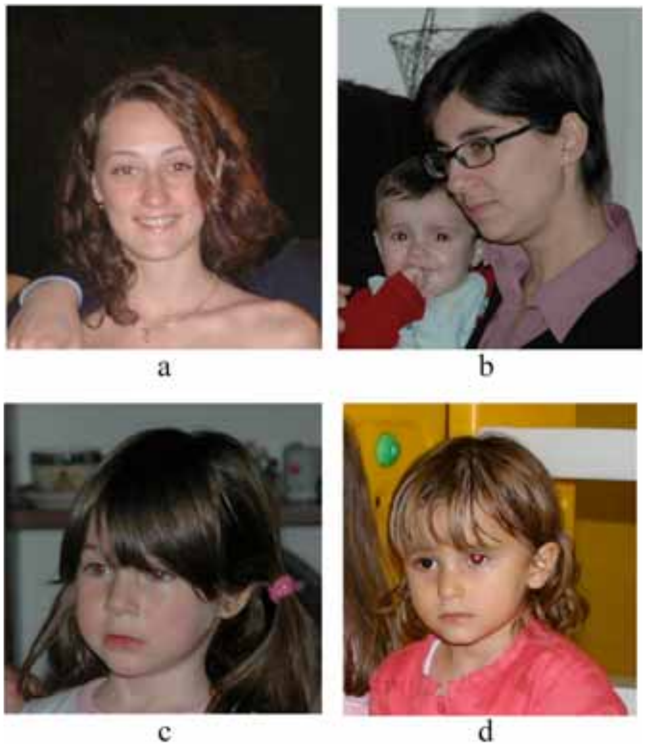

Fig. (1). Example of redeye defects. Note the different color of the artifact in different images. (**a**): typical example of an image redeye affected. (**b & c**): examples of images where eyes are partially occluded by hair or glasses. (**b & d**): images showing non-paired red eyes.

consider the correction of candle lights as if they were redeye artifacts or the correction of only one of the two red eyes in the same face.

Most of the literature methods have been patented mainly by big companies. Among these methods, several describe algorithms to correct redeye automatically, once a user has defined the region where the redeye is present, [1-4] while others describe methods that also include automatic detection of the redeye artifact location, [5 -11].

Dobbs and Goodwin of Eastman Kodak Company were probably the first to propose a mechanism for recoloring a selected region of a digital image, and in particular redeye, [1]. The target color as well as other parameters of the color correction is user controlled.

Benati *et al.*, [2, 3], with respect to the previous Kodak patent reduce the user intervention because only the general region of interest is required. They also introduce a more neutral appearing correction, classifying eye pixels in three different categories, body pixels, border pixels and glint pixels. Again for the Kodak Company, Schildkraut *et al.*, [5] further develop the previous Kodak patents and present a fully automatic method, able to detect and correct redeye pairs without any user intervention. This is obtained by using eye and face detection technologies and a large number of features to distinguish between true redeye pairs and other small red content in the image [6, 12].

In the first patents of Hewlett Packard, Patti *et al*., of in 1998, [13, 4], have described a process to correct redeye artifact with minimal user intervention. The user only has to select a box around each eye. They were probably the first to enhance the redeye artifacts, highlighting their redness, to better locate the red pupil. Still for Hewlett Packard, Wang and Zhang, [7] in 2001 have realized an automatic detection and reduction system. The redeye detection module uses face and eye detection technologies such as neural networks [14], and principal component analysis. The red pixels of the detected pupil are changed in the reduction module into a predetermined color, which can be either black or gray.

Another automatic redeye detection and correction procedure for the same company is described by Gaubatz and Ulichney, in 2002, [8]. In their work, faces are detected with a cascade of multi-scale classifiers [15, 16]. To emphasize redeye regions, they define a measure of the redness as the ratio between the energy of the red component and the energy of the remaining components. Starting from these previous works, in late 2003, Ulichney *et al*., [17], developed a one-click system called '*RedBot*', available free online [18]. Further refinements of their procedure are presented in [19].

The most recent redeye solution for HP, consisting of a two module procedure (redeye detection and correction), is described in the work of Luo *et al.*, [9, 20, 21]. The redeye detection part is modeled as a feature based object detection problem, which uses Adaboost algorithm [22] to simultaneously select relevant features and assign feature weight for the classifier. A systematic, orientation independent feature computation scheme for object detection is adopted, which can detect red eyes of arbitrary in-plane rotation. In the redeye correction step, an adaptive redeye recoloring algorithm is applied to perform desaturation and darkening over the redeye region. An implementation of these algorithms in HP's Photosmart R707 digital camera, led to an in-Camera Red-Eye Removal, which instantly removes red-eye from photos while they are still in the camera, without using a PC and graphics software. Hardeberg *et al*., [23, 24] at the beginning proposed a semiautomatic method where the redeye region is manually selected. In more recent works, [25, 10], they have improved this semiautomatic approach and developed a fully automatic method that also has a US patent, [11]. The final algorithm consists in a preliminary color segmentation based on thresholding in color spaces to locate the skin regions. The pupil areas, supposed to be approximately circular, are better located within the region with higher redness with an edge detection technique based on a series of convolution masks.

Also based on a gray-scale conversion of a red-enhanced image is the method proposed by A. Held of Gretag Company, [26]. The search space for the redeye location is consecutively reduced by taking into account image semantic information, and the detection of the eye centers is based on the Hough transform. The main problem with this method is that it requires an iris of sufficient size and clarity.

Jeoffe *et al*., of Fujifilm Company, [27, 28], have developed a redeye detection procedure, based mainly on computer vision and machine learning techniques.

Gasparini and Schettini, [29], have designed a modular procedure for automatic detection and correction of the redeye effect, specifically designed for uncalibrated images, such as images acquired by unknown systems under unknown lighting conditions. Firstly they apply an adaptive color cast removal algorithm to correct the color photo. This phase not only facilitates the subsequent steps of processing, but also improves the overall appearance of the output image. Then the method looks for redeye within the most likely face regions, obtained combining a color-based skin detector with a face detector based on a multi-resolution neural network.

Approaches not based on face detection were developed by Wan *et al*., [30] and by Volken *et al*., [31]. Wan *et al.*, have developed a method based on a statistical approach called Active Appearance Models (AAM) which is able to model a deformable object shape. Volken *et al.* instead, have based their work mainly on image processing and heuristics.

Of relevant importance are recent methods that give major attention to the correction step. In fact, most of the methods cited above, adopt a yes/no decision by applying either no or the maximal possible correction. This approach can lead to severe mistakes, such as completely missing red eyes, introducing disturbing artifacts or performing unnatural corrections. Ulichney and Gabautz, [32, 33] were the first to consider the correction of red eye defects with a perceptual based approach. The common solution of de-saturating the red eye defects usually leaves the region gray, and much lighter than what would appear natural. In order to solve this question, they perform a perceptual study designed to find the most visually pleasing target luminance for corrected images.

Willamowski and Csurka, [34, 35], have developed a probabilistic approach based on stepwise refinement of a pixel-wise red eye probability map. The correction step applies a soft red eye correction based on the resulting probability map.

Marchesotti *et al.*, in particular, have closely considered the problem of red eye correction, [36]. They have proposed three correction methods, evaluating what they have called their *image degradation risk* and their *expected perceptual quality improvement*. An adaptive system is applied to select the correction strategy dependent on these measures and on the red eye detection confidence.

REDEYE DETECTION

There are two main approaches for redeye detection. In one case the search space is reduced either by manually selecting the eye regions or adopting, for instance, classifiers to identify faces, eyes or skin regions where the successive detection of red eyes concentrate. There are several modules that can reduce the domain to be searched. These modules are often based on general purpose methods, because they do not necessarily need any knowledge about red eye in particular. These modules can be combined in several ways (flowchart of Fig. **2**)

In the second case, the red eyes are directly detected by scanning the whole image without a previous reduction of the search space (flowchart of Fig. **3**). In both cases initial candidate redeye regions are generally submitted to further verification steps (flowchart of Fig. **4**), to obtain a final confirmation, generally based on color, contrast, geometry, presence of skin, sclera, glint, etc. and/or verifying that the candidate red regions belong to eyes obtained adopting proper eye classifiers.

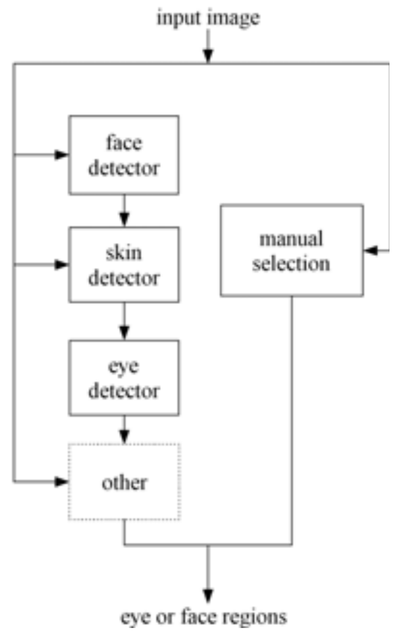

Fig. (2). Flowchart of possible combining of modules for the reduction of the search space for redeye detection.

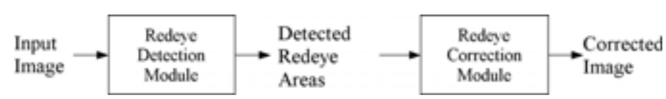

Fig. (3). Main flowchart in case of direct search of redeye regions.

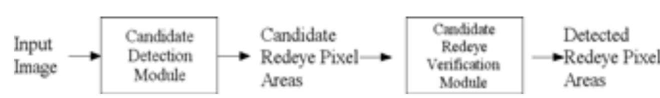

Fig. (4). Redeye detection module, consisting on a candidate detection module and a subsequent redeye verification step.

Among those who have first tried to reduce the search space and then look for red eyes, Schildkraut *et al*., [5, 6, 12], developed an automatic detection modules using face and eye classifiers.

Wang and Zhang [7] use neural network to detect faces and eyes. Gaubatz and Ulichney [8] reduce the search space looking for faces with the aid of a cascade of multi-scale classifiers [15, 16]. Hardeberg *et al*., perform a preliminary color segmentation based on thresholding in color spaces to locate the skin regions US patent, [11].

Based mainly on computer vision and machine learning techniques, Jeoffe *et al*., of Fujifilm Company [27, 28], first detect all the possible redeye candidates in the image, then reduces the false positives with a face detector, and finally find the redeye boundaries with a learned classifier. All the three detectors are automatically learned from data using Boosting.

Gasparini and Schettini [29] combine the results of a color-based face detector and of a face detector based on a multi-resolution neural network, to obtain the most likely facial regions. Red eyes are searched for only within these regions, seeking areas with high redness satisfying various geometric constraints.

Wu [37], first determines skin areas within an image. Then all the inner edges within the skin regions are detected. These boundaries are matched with an eyelid quadratic curve to determine the location of the eyelid areas. Then the procedure looks for red pixels within these regions. A further quadratic curve model can be applied to localize an iris area to improve the red eye localization.

An example of a strategy that combines modules that are commonly involved in redeye detection procedures, in a slightly different order is presented by Nanu *et al*., [38].

They initially detect in parallel red eyes and faces within the original image. Then they identify those detected faces that include only one detected red eye. Within these faces, using less stringent search criteria they detect additional red eyes. Finally they combine the directly detected red eyes with those detected within a face. A flowchart depicting this approach is reported in Fig. (**5**).

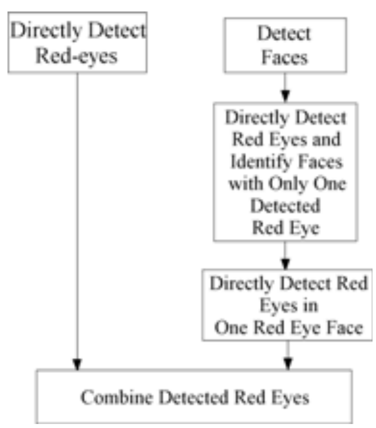

Fig. (5). Flowchart of the main detection approach of Nanu *et al.*, [38].

Looking directly for red eyes, Wan *et al*., [30] have developed a method based on Active Appearance Models (AAM). AAM is a statistical approach which can model a deformable object shape. Joining color information and a deformable model they locate red eyes as deformable objects. Volken *et al.*, [31] base their work on image processing and heuristics. They first look for the red zones of the whole image, then estimate the probability of each of these zones being a red eye by evaluating their roundness, the amount of white around these zones, corresponding to the sclera and the amount of skin.

In the method developed by Zhang *et al*., [39] they find pixels of the whole image that may be marked as a red color or non-skin color pixel. To restrict red color areas, the algorithm proceeds to remove invalid regions by size and brightness restrictions and checks the surrounding non-skin pixels. Finally, an eye classifier is utilized to confirm each candidate region found in the previous steps. Only those regions confirmed by the classifier as human eyes will be passed to the auto-correction stage.

Several approaches use skin tone to limit a posteriori the false positive red eye candidates in a map of red patches. Luo *et al*., [21] after a preliminary screening where global candidate red eye areas are detected mainly on the base of redness and contrast, perform several local verification tests. In particular, each candidate red eye area that does not correspond to an isolated non-skin tone 'island' in a skin tone region is filtered from the final red eye map.

Slightly different from the schemes presented, Zhang *et al*., [39] adopt a heuristic algorithm looking for a group of candidate red regions. An eye classifier is then utilized to confirm whether each candidate region is a human eye or not.

RED EYE DETECTION MODULES

Usually the redeye detection modules start with a color space conversion to facilitate segmentation of redeye pixel from non redeye pixels. The color space adopted is generally chosen to reduce the overlap of the color distribution of actual redeye pixels and the color distribution of skin pixels, and thus the distribution of the redeye colors and skin colors may be easily separated.

Several approaches adopt a non-standard color transformation, so that the red eye pixels are enhanced to better localize the red pupil to be corrected. In general this transformation produces a gray level image, defined as the redness map. Patti *et al*., [13, 4] were probably the first to highlight the red pixels using a non standard luminance chrominance representation but several different transformations can be adopted. Most of these methods are based on measuring the pixel redness, evaluating the ratio between the pixel red component energy and the total pixel energy (Gaubatz and Ulichney [8]), eventually defining proper weighting factor for the three different r,g and b components.

Smolka *et al*., [10] have adopted the difference between the red channel and the maximum of the other two channels to enhance the redness of the redeye defect.

Luo *et al*., [21], in their last patent report several possible measures for redness, summarizing most of the measures adopted by other inventors.

In Table (**1**) some of the simpler redness maps are reported, among all the possible definitions.

To obtain the parameters to segment redeye candidate regions generally sample images of actual red eyes are manually labeled to generate sample data. Then to obtain the redeye color parametric thresholds, a histogram analysis can be performed or other more complex quantization methods can be used (i.e. k-means quantization process.). The redeye color boundary corresponds to a multi-dimensional surface in the adopted color space.

Table 1. Simple Redness Definitions and their References

Authors	Redness
Luo *et al*. [21]	$\frac{\alpha R+\beta G+\gamma B}{R+G+B+d}$ (α= 104; β=-153; γ=51; d=1) ----------------------------------- $\frac{r^2}{(r+g+b+1)^2}$ ----------------------------------- $\frac{r^2}{(g+b)^2}$ ----------------------------- $\frac{Cr}{(Cb+1)^2}$
Gabautz *et al*. [8,19]	$\frac{R^2}{(G^2+B^2+k)}$ with K=14
Held [25]	$R-\min\{G,B\}$
Smolka *et al*. [10]	$\frac{R-\max\{G,B\}^2}{R}$
Gasparini and Schettini [29]	$\max\left\{0,\frac{2R-(G+B)}{R}\right\}^2$

Usually the strategy used to identify redeye pixels is recall oriented to get the set of classified pixels overly inclusive. Than candidate validation modules tend to reject false alarms increasing the accuracy, to obtain pixels that are highly likely to belong to an actual redeye.

For example, Luo *et al*., [21] define two redeye color surfaces in the CIE Lab color space, a high contrast color surface and a low contrast color surface. The high contrast boundary curves are used to aggressively separate redeye color pixels from non redeye color pixels. On the other hand, the low contrast boundary curves are used in a less aggressive segmentation, in order to accommodate cases of redeye pixels somehow merged within non-redeye pixel areas (e.g. regions of pale or reddish skin). Both high and low contrast surfaces are used to detect candidate redeye pixels, and the successive segmentation and validation processes reduce the false alarms. They have also observed that the process of detecting red eyes using multiple redeye color models and/or a redness map, and merging the results, frequently improves the overall redeye detection accuracy.

REDEYE VALIDATION PROCESSES

In most of the cases the preliminary step in the validation process consists of a segmentation that produces candidate redeye areas starting from candidate redeye pixels.

This phase is generally performed using one of the known algorithms based on pixel connectivity.

Several criterions can now be adopted to validate the candidate redeye regions obtained.

- geometric constraints satisfaction
    - shape: for example atypical elongated candidates redeye are rejected.
    - relationship between sizes (aspect ratio eye/face), distances and proportions of pair of candidate red eyes;
- redeye pair verification, [12]
    - size: in particular differences in size of the two eyes of the considered pair or comparison between redeye pupil and iris sizes.
    - distance between the two candidates
    - grayscale differences of the two candidates
    - color differences of the two candidates
- presence of glint, which is the specular reflection of the flash in the eye [19, 39, 36]
- presence of sclera [31]
    - sclera/eye ratio
- percentage of skin tone in the neighborhood of the candidate red eye [31, 21]
- iris detection [37].

The criterions cited above can be combined to obtain the likelihood of a redeye region or the criterions can be verified in cascade to successively reduce the candidate regions.

Gaubatz and Ulichney [8] together evaluate intensity, redness and eye size to put constraints on the search space. Moreover, to avoid the introduction of new artifacts, they further consider geometric constraints on the pupil boundaries and they introduce a correction factor to limit abrupt variations.

Luo *et al*., [21] have developed a verification module based on the analysis of multiple features in parallel, using a machine learning framework. They firstly apply a single-eye verification classifier and then a pairing verification one. They adopt an Adaboost based machine learning model [22] to simultaneously perform feature selection and classifier training. In the single-eye verification classifier they mainly adopt grayscale features and color features, and they use a skin tone classifier to evaluate the percentage of skin tone pixels in the neighborhood of the candidate redeye.

REDEYE CORRECTION

Once the red eyes are detected, a color correction of the artifact is applied. It seems that this part of the problem is easier than the detection step. Actually several aspects must be taken into account to avoid degradation of the original images. The main guidelines in color correction are:

1. preserve the glint, the specular reflection of the flash in the eye, that gives the eyes a natural aspect;
2. correct both red eyes (if present) with the same strength and color;
3. avoid abrupt variation between the corrected and the uncorrected areas.

In most of the approaches, if a pixel has been detected as belonging to a redeye, it is replaced with a substantially monochrome pixel. Several strategies more or less complicated, can be adopted to obtain this natural correction.

The simplest approach was performed by Wu [40], where the red color of the defected eyes is simply substituted by black. Corrections of this type could be very dangerous leading to a processed image which is even worse than the defective original.

Patti *et al*., [13, 4] perform another simple neutral correction, assigning to the red area a gray value of 80% of the original luminance. With this scaling factor experimentally evaluated, the glint in the pupil is preserved.

Usually the correction is done by applying a weighted desaturation to smooth the perceived edges due to hard decision boundaries, Gabautz *et al*., [8].

This can be done with the aid of a smoothing mask as suggested by Smolka *et al*., [10] to achieve a softer correction that should appear more natural.

An example of a possible monochrome correction, as reported in [29] is:

$$R_{new} = R_{old} \times \left(1 - Mask_{smooth}\right) + Mask_{smooth} \times R_{mch}$$
$$G_{new} = G_{old} \times \left(1 - Mask_{smooth}\right) + Mask_{smooth} \times G_{mch}$$
$$B_{new} = G_{old} \times \left(1 - Mask_{smooth}\right) + Mask_{smooth} \times B_{mch}$$

The coordinates of the monochrome pixel are R_{mch}, G_{mch} and B_{mch}, evaluated considering the intensity equal to the mean of (G, B) and the color correction is weighted with the smoothing mask ($Mask_{smooth}$). The correction mask can be considered as the map of the probability that a certain pixel belongs to a red-defect region or not. Pixels approaching to the eye boundaries receive a gradually decreasing probability, allowing for a smooth change between correct and uncorrected regions.

Luo *et al.*, [21] propose a method to detect and correct redeye areas starting from different resolutions of the original image. In particular, the correction is adapted to the prescribed output resolution. For example, in a printer system application, the detected eye could be scaled up from a thumbnail size of about 384 pixels in width by 288 pixels in height, to a print image size of 1800 pixels in width by 1200 pixels in height.

They propose strategies to compensate errors that might occur as a result of the inaccuracy inherent in the quantization process involved in mapping areas from small resolution to higher resolution. To refine the final area, if necessary, they propose a further pixel classification based on skin tone analysis.

Redeye pixels are then corrected desaturating and darkening the original color. The darkening factors are computed based on luminance values of the input image pixels. These factors decrease with the darkness level of the pixels; that is, lower luminance values (i.e. darker pixels) are associated with lower darkness factors. Moreover, redeye pixels near the center of the redeye correction region are assigned higher weights than redeye pixels near the boundaries.

EVALUATION OF THE REDEYE DETECTION AND CORRECTION PROCESSES

Fixing redeye is a two step problem. It seems that the overall performance of any system could be analyzed considering separately the performance of the detection and the correction modules, than combining these evaluations. In fact, the redeye correction is strongly correlated with the output of the detection module as clearly underlined by Marchesotti *et al*., [36], thus the analysis of the performance of the detection must take this dependency into account.

To evaluate the performance of the detection module, the following machine learning terms are usually adopted:

- True Positive (TP): effective red eyes detected
- False Positive (FP): non-red eyes erroneously detected as red eyes
- False Negative (FN): red eyes erroneously missed

Considering that redeye correction is based on the output of the redeye detection, it will become clear that not all the FPs have the same weight evaluating the overall performance of the system. In fact, they can correspond to false detections in the background that are usually less damaging, or false detections within faces (typically, nose, lips, part of the mouth), leading in this case to severe degradation of the original image [36]. Another error in the detection phase that could have serious consequences in the correction step is poor segmentation of the redeye region. In particular, the worst cases correspond to over-segmentations. Note that these errors are not considered using the standard machine learning analysis.

Moreover, also FNs have different importance in the overall evaluation. In fact, it would be worse to miss one of two red eyes correcting only one eye, than to miss both the red eyes of the same person.

In Figure **6** the result of the application of an automatic detection and correction algorithm is presented, showing the consequences of different errors in the overall process. In the original image, Fig (**6a**), three children are depicted. The two children on the right both show a redeye pair. In Fig (**6b**) the detail of the child on the right is reported. The pair of red

Fig. (6a). Original image redeye affected, where the two children on the right, both show two red eyes. (**b**) The pair of red eyes are detected and corrected. The right eye still shows a low level of redness, thus the color correction produces two slightly different eyes. For this child the performance of the detection was perfect, while the performance of the correction less successful. (**c**) Only one of the two red eyes was detected and thus corrected. The performance of the detection is low, while the correction is successful. (**d**) A false positive in the detection implies a wrong correction in a face region which corresponds to a serious damage.

eyes are detected and corrected. Thus we have no FPs, and all the TPs. The right eye still shows a low level of redness, thus the color correction produces two slightly different eyes. For this child the performance of the detection was perfect, while the performance of the correction was less successful. In Fig (**6c**) the child in the middle is considered. In this case only one of the two red eyes was detected and thus corrected, obtaining one TP, one FN and no FPs. The performance of the detection is low, while the correction is successful. Finally in Fig (**6d**) the child on the left is reported. In this case a false positive in the detection implies a color correction in a face region which is a severe error.

In Figure **7**, images showing the effect of FP correction are presented. On the left, Fig. (**7a** & **c**) the original images are reported, while on the right Fig. (**7b** & **d**) the corrected ones (respectively c and d) are depicted. In Fig. (**7b**), the FP on the glass, i.e. in a background region, is corrected, but this error does not seem severe, and in any case less damaging than a correction on a face, as in Fig. (d. In the second image, Fig. (**7d**), the two FPs (still in the background) after the color correction could be considered as a severe error only for those who know that the original color of the buttons was red.

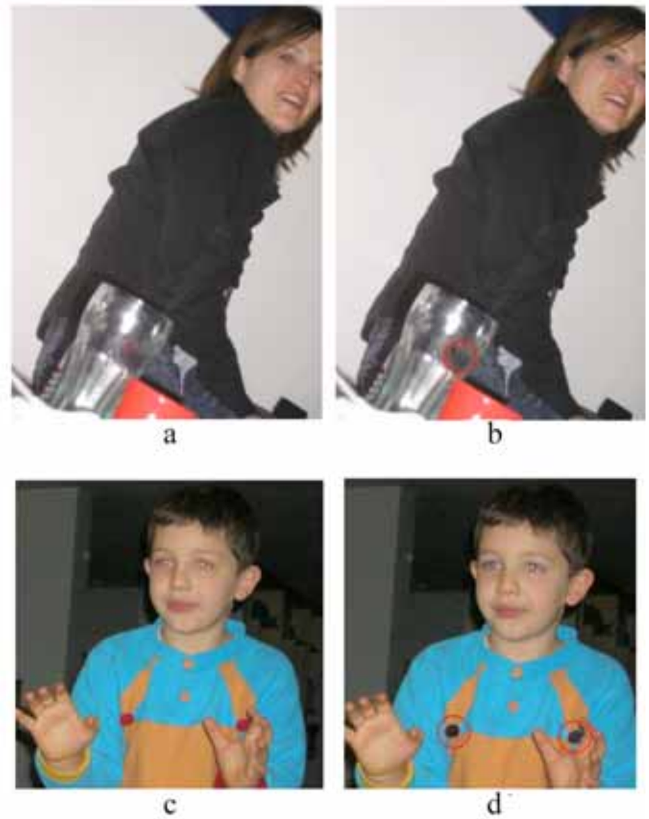

Fig. (7). Images showing the effect of correction of FPs. On the left the original images (**a & c**), on the right the corrected ones (respectively **b & d**). In the first row, the FP on the glass, i.e. in a background region, is corrected (Fig. **b**), but this error does not seem severe, and in any case less damaging than a correction on a face, as in Fig. (**6d**). In the second image (second raw) the two FPs (still in the background) after the color correction could be considered as a severe error only for those who know that the original color of the buttons was red (Fig. **d**).

Note that the color correction of the red eyes is successful in the case of figure **7a**, as shown in Figure **7b**, while in the case of Figure **7c** it is poor (see Figure **7d**). This is due to the original color of the defect. Red eyes with a highly saturated redness or a huge glint region are more difficult to correct by most of the methods available. Examples of eyes showing this defect are reported in Figure **8**. Luo *et al.*, [21] tried to solve this problem, also darkening part of the pixels within the glint region (or in the saturated region), in accordance with a darkening factor, which is function of the distance from the center of the glint.

Only until recently have few works in the literature reported the development of a procedure with a correction strategy that depends on the detection results.

Marchesotti *et al.*, [36], have considered the different kinds of detection errors, and in particular they have clearly underlined that different correction techniques will have different impacts on these errors. They have evaluated what they have called *image degradation risk* for given approaches when correcting different kinds of errors. They have proposed three correction methods with different levels

a b c

Fig. (8). Examples of images with a highly saturated redness that generally causes poor color corrections.

of image degradation risk and expected perceptual quality improvement. They have developed a detection module that provides a confidence measure of a given region to be a red eye. When this confidence is high, a more rewarding strategy is chosen, while a conservative method is preferred for low confidences where the degradation risk has to be decreased. For a medium confidence a method is selected which offers a good compromise between reward and degradation risk.

Nanu *et al*., [38] developed detection strategies that are trained with respect to the possible detection results. They divide red eyes into two categories:

- A Category: faces containing pairs of red eyes. (between 70% and 90% of relevant images)
- B Category: faces containing a single red eye. (between 10% and 30 of relevant images)

The detection results are divided as follows:

A1: detection of both red eyes in faces of A Category;

A2: missing of both red eyes in faces of A Category;

A3: detection of a single red eye in faces of A Category

B1: detection of the single red eye in faces of B Category

B2: missing of the single red eyes in faces of B Category

They present a solution that tries to increase the paired redeye detection by reducing A3 and keeping B1 high. Alternatively they also propose a solution to reduce A2, A3 and B2, while keeping B1 high.

I. Safonov *et al*., [41] have recently proposed a numeric quality criterion of automatic redeye correction. They have applied this metric to determine the parameters of a method of automatic redeye detection and correction.

This quality metric is constructed by applying the Analytic Hierarchy Process (AHP) to consumer opinions about correction outcomes. In defining this quality metric they start from an analysis in terms of FPs and FNs. As in [36], they divide FPs into two groups critical FP and non-critical FP. Considering that the visibility and the need for correction of various types of red eyes are different, they also distinguish FNs among regions which are mandatory for detection; and regions which are desirable for detection. They also consider the unwanted situation of correcting only one eye of a pair. As regards to correction, they distinguish two cases: irritating cases when corrected eyes look worse than the original ones and cases when correction is noticeable but not irritating.

Comparing the performances of all the different detection and correction strategies for redeye removal is really challenging. In fact there not exists a reference database. Moreover the analysis of the results is performed in several different ways, thus the results reported by the authors in their papers can not be directly compared.

CURRENT & FUTURE DEVELOPMENTS

Fixing redeye is a two step problem, detection and correction. The detection of redeye artifacts has been exhaustively analyzed using different strategies. The performance of this step strongly depends on the performance of the methods adopted either to reduce the search space or to directly detect red eyes. Further improvements are still required in the correction phase, where several aspects must be considered, such as the quality of retouching, and the risk of image degradation due to the correction of false alarms. The mutual interaction and trade off between these factors would require further studies and deeper understanding of image content.

A significant improvement in the redeye removal field would be the definition of a reference dataset of images where all the strategies can be fairly compared. This dataset should be acquired with several cameras and thus should present a wide variability in terms of quality and resolution and in the color of the defects. Moreover a reference quality metric should be defined and adopted. This metric should combine the performances of both the detection and of the correction steps, taking into account the different relevance of false positives within different image regions.

Another emerging issue that should be further addressed concerns peteye color correction. Automatic peteye color correction is significantly more difficult than human redeye removal, both in the detection and in the correction step. In fact shape, color and in general other possible features to describe the pet face show a greater variability than in case of human face. Thus face detection algorithms would not be probably successful as a strategy for search space reduction. Moreover, the pet retina has a special reflective layer that causes several different eye color,s depending not only on the pet genre or race, but also on animal's age, fur color, etc.

Preliminary studies on fixing peteye colors have been carried out by Yen *et al*. [42].

CONFLICT OF INTEREST

Paper has no conflict of interest

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