Towards automatic redeye effect removal

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Abstract

The redeye effect is typically formed in amateur photographs taken with a built-in camera flash. Analysis of the available techniques and products indicates that their efficiency in correcting this artifact is limited and their performance is inconsistent. In this work we propose a user friendly solution, which could be used to restore amateur photographs. In the proposed method the redeye effect is detected using a skin detection module and eye colors are restored using morphological image processing. The new method is computationally efficient, robust to parameter settings and versatile, as it can work in conjunction with a number of skin detection methods.

Keywords: Redeye removal; Skin detection; Restoration; Color image enhancement

1. Introduction

The redeye effect is caused by light entering the subject’s eye through the pupil and reflecting from the retina. The light is usually coming from the flash, which is used when taking the photographs. The redeye artifacts are a well-known problem in amateur photography. Otherwise good photographs are often completely unacceptable because of a glowing red color that appears in the eyes of people photographed with flash bulbs (Nguyen et al., 2002). This is particularly the case with photographs of babies and children. With the advent of digital imaging technology, new possibilities arise for solving this problem, using the techniques of image processing. Several commercial imaging software packages have offered the function of redeye removal in different forms and with different degrees of success (Hardeberg, 2001). Outside of the patent literature (Benati et al., 1995, 1998; Dobbs and Goodwin, 1992; Lin et al., 2000) however, there is not much published on this subject. Prior to this work, only a few conference presentations (Czubin et al., 2002; Hardeberg, 2001; Patti et al., 1998) and one journal paper (Hardeberg, 2002) were published.

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Possibly the first image processing algorithm for redeye removal was proposed by Dobbs and Goodwin (1992). In their algorithm, the user first had to zoom in on the picture and select the pixel that best represents the redeye artifact to be corrected. Then, neighboring pixels were modified to remove the red hue if they belonged to a discriminator ellipse defined in the chrominance plane of the YIQ color space. Later, Benati et al. (1995, 1998) proposed a new method, in which the level of the user interactivity was significantly reduced.

Hardeberg (2001, 2002) proposed a method to correct the redeye artifacts, in which an image mask is computed by calculating a colorimetric distance between a prototypical reference redeye color and each pixel of the image containing this artifact. Morphological operations are applied to the binary mask, followed by a blob analysis technique to group the pixels of the mask into eight-connected components. The blob that has the highest probability of representing a redeye artifact, based on its size and shape is chosen. At the last stage the mask is smoothed, to achieve a softer correction that appears to be more natural to the human viewer.

In (Lin et al., 2000; Patti et al., 1998) an automatic digital redeye reduction algorithm was proposed. The authors used a nonstandard luminance–chrominance representation to enhance the regions affected by the redeye artifact. After the detection of a block of maximal area, thresholding operation and a simple color replacement structure are utilized to complete the task.

Many approaches such as these, set the stage for technologies that have become increasingly important in the area of digital cameras. It is however, unfortunate that the systems currently available exhibit a high level of heterogeneity in their technologies. In this work we propose a user friendly solution, which could be applied for the restoration of the amateur photographs and could be incorporated directly into the digital camera acquisition system. The modularity and versatility of the proposed scheme can thus serve as the blueprint for the creation of redeye effect removal schemes, since it is able to combine any number of face and pupil detection methods.

The paper presented here is organized as follows. In Section 2 the proposed redeye effect removal algorithm is introduced. The motivation and design characteristics are discussed there in detail. The paper then closes with experimental results and conclusions in Sections 3 and 4.

2. New algorithm description

The proposed algorithm of the redeye correction consists of the following steps:

1. Detection of the objects’ skin in the color image with fast segmentation algorithms based on thresholding in color spaces.
2. Processing of the binary image depicting the skin-like regions with the methods of mathematical morphology.
3. Conversion of the color image into a gray-scale representation enhancing the color of the redeye region.
4. Detection and segmentation of the image parts affected by the redeye effect in the skin regions.
5. Color replacement of the redeye to obtain a natural eyes and face appearance.

2.1. Skin detection step

The problem of skin detection in digital images has received a considerable amount of interest in recent years due to numerous practical applications. Despite the large amount of research performed on the detection of human skin in scenes with complex background, it still remains a difficult problem of pattern recognition (Chellapa et al., 1995; Garcia and Tziritas, 1999; Herodotou et al., 1999; Plataniotis and Venetsanopoulos, 2000; Wu et al., 1999; Yang and Huang, 1994; Yang et al., 2002).

Color is a key feature used to understand and recollect the contents within a scene. It is found to be a highly reliable attribute for image retrieval, as it is generally invariant to translations, rotation and scale changes. In our approach we use color as the primary tool in detecting and locating the skin regions in a scene with complex background.
The results of the research performed on the skin detection show that (Chellapa et al., 1995; Herodotou et al., 1999; Yang et al., 2002)

(a) Human skin colors are clustered in the chromatic color space.
(b) Skin color distribution of a person occupies a relatively small area within the color space.
(c) Skin color differences can be reduced by intensity normalization.
(d) Under certain lighting conditions the skin color distribution can be modelled by a multivariate normal distribution.
(e) The skin-like regions differ more in brightness than in chromaticity.

However, when the image depicting skin regions is taken under varying lighting conditions in a scene with a complex background, the skin detection algorithms may fail. It is well known that changes in the spectral composition of the scene illumination cause severe problems in effective skin detection and localization (Storring and Granum, 2002).

The skin chromaticity distribution of an individual under constant illumination conditions may be approximated as a multivariate Gaussian distribution in the red–green chromaticity plane. In order to better estimate the skin color distribution, the mixture of Gaussians can be used to model its shape in different color spaces.

In the presented method of redeye correction we have used the normalized rgb color space and the well known HSV model to locate the skin-like image regions.

2.1.1. Skin segmentation in the rgb color space

One of the most widely used color models is the RGB representation in which different colors are defined by combinations of red, green and blue primary color components. Since the main variation in skin appearance is largely due to luminance component, the normalized rgb color space is generally preferred to filter out the dependence on the image illumination.

For the analysis of colors independent of the their intensities, it is convenient to transform the RGB values into their corresponding chromaticities \( r, g, b \) defined as (Plataniotis and Venetsanopoulos, 2000): 
\[
    r = cR/I, \quad g = cG/I, \quad b = cB/I,
\]

\[
    I = R + G + B, \quad \text{where} \quad R, G, B \in [0, 255], \quad \text{and} \quad c \text{ is a constant, (we will use } c = 100). \quad \text{The normalized color values can be expressed using only } r \text{ and } b \text{ as } g = c - r - b \text{ and the normalization makes the } r, g \text{ variables nondependent on the brightness } I.
\]

The distribution of the pixels which represent the tone of the skin can be modelled as a two-dimensional Gaussian in the \( r, g \) space (Sirohey et al., 2002). Sirohey and Rosenfeld selected manually portions of 72 images from the Aberdeen database representing the face area and as a result of the statistical analysis they obtained the following parameters of the Gaussian distribution (mean value \( \mu \) and covariance \( \Sigma \)) (Sirohey et al., 2002),

\[
    \mu = \begin{bmatrix} 42.91 \\ 32.28 \end{bmatrix}, \quad \Sigma = \begin{bmatrix} 19.28 & 5.45 \\ -5.45 & 8.55 \end{bmatrix}. \quad (1)
\]

Another experiment performed using their own database of 21 images gave slightly different results

\[
    \mu = \begin{bmatrix} 52.66 \\ 29.99 \end{bmatrix}, \quad \Sigma = \begin{bmatrix} 68.94 & -30.89 \\ -30.89 & 18.11 \end{bmatrix}. \quad (2)
\]

Wang and Yuan (2001) performed the statistical analysis of the color distribution of the face pixels using a database of 30 images and obtained the following values of the range of the \( r \) and \( g \) components: \( r \in [36, 46.5], \quad g \in [28, 36.3] \).

Storring and Granum (2002) examined the distribution of the human skin chromaticity of an Asian subject under varying illumination conditions and their research show a strong dependence on the correlated color temperature (CCT) of the light illuminating the scene. The \( g \) component is only slightly dependent on the CCT and the mean of the \( g \) component lies in the \([0.3, 0.35]\) range. However, the \( r \) chromaticity depends heavily on the CCT and the cluster mean was at about 0.3 for CCT 6200 K and 0.6 for CCT 2600 K.

The difficulties in determining the optimal bounds for the \( r, g \) values, which could enable good classification of the face-like regions are also confirmed by our own experiments. Fig. 1 depicts three sets of collections of skin patches taken randomly from the faces of different images from
different Internet resources,\(^2\)\(^-\)\(^5\) together with the two-dimensional \(r, g\) histograms. The shape and location of those histograms confirm that it is difficult to set optimal threshold values, which encouraged the authors of this work to use also the \(HSV\) color space to make the thresholding results more precise.

### 2.1.2. Skin segmentation in the \(HSV\) color space

As it is commonly recognized that the \(HSV\) model is also very well suited for the description and analysis of the skin-like regions, we also made use of this color space. For the conversion from \(RGB\) to \(HSV\) (hue, saturation and value) we used the following equations (Plataniotis and Venetsanopoulos, 2000)

\[
H_1 = \cos^{-1}\left\{ \frac{0.5[(R - G) + (R - B)]}{[(R - G)^2 + (R - B)(G - B)]^{1/2}} \right\},
\]

\[
H = H_1 \quad \text{if } B \leq G, \quad H = 360 - H_1 \quad \text{if } B > G,
\]

\[
S = \frac{\max(R, G, B) - \min(R, G, B)}{\max(R, G, B)},
\]

\[
V = \frac{\max(R, G, B)}{255}.
\]

Wang and Yuan (2001) analyzed the skin portions of a database, which consisted of 30 images and obtained the following optimal range of the \(H, S, V\) values: \(H \in [0, 50], S \in [0.2, 0.68], V \in [0.35, 1]\).

Herodotou et al. (1999) analyzed the clusters of pixels from the facial regions and obtained the following ranges: \(H \in [0, 50] \cup [340, 360], S \in [0.2, 1], V \in [0.35, 1]\), which are in good consistency with the previous results, taking into account

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\(^3\) Breakfast for Champions Database, http://www.libfind.unl.edu/alumni/events/breakfast_for_champions.htm.
\(^5\) Psychological Image Collection at Stirling (PICS), University of Stirling Psychology Department, http://pics.psych.stir.ac.uk/.
that this range was chosen to be quite wide, so that a variety of different skin types could be modelled.

Tsekeridou and Pitas (1998) obtained the following thresholds for efficient facial skin detection: \( H \in [0, 2.5] \cup [3.5, 3.6] \), \( S \in [0.2, 0.6] \), \( V \in [0.4, 1] \). The hue \( H \) range restricts segmentation in reddish colors and the saturation \( S \) range excludes pure red or dark red colors.

Sobottka and Pitas (1998) obtained good results applying the following thresholds:

\[
H \in \begin{cases} 
0 & \text{if } H \leq 0.50 \\
340 & \text{otherwise}
\end{cases}, \\
S \in [0.23, 0.68], \\
V \in [0.35, 0.75]
\]

Finally, Garcia and Tziritas (1999) after a statistical analysis performed on facial regions taken from a database of 950 skin samples gave the following bounds for the \( H \), \( S \) and \( V \) values

\[
S \geq 10; \quad V \geq 40; \quad S \leq -H - 0.1V + 110; \quad H \leq -0.4V + 75; \\
\text{if } H \geq 0 \quad \text{then } S \leq 0.08(100 - V)H + 0.5 \\
\quad \text{else } S \leq 0.5H + 35.
\]

As there is no common agreement on how to set the optimal threshold levels for the \( rgb \) and \( HSV \) space and in order to fully exploit the advantages of the two color spaces and to diminish the influence of the illumination conditions, we decided to combine the outputs obtained when thresholding the image both in the \( rgb \) and \( HSV \) space. This approach proved to yield much better results of skin detection under various illumination conditions with fewer amount of regions, which were classified as skin-like but in fact did not represent human skin.

Taking into account the results obtained in the experiments described above (Garcia and Tziritas, 1999; Herodotou et al., 1999; Hsuy et al., 2002; Sobottka and Pitas, 1998; Tsekeridou and Pitas, 1998; Wang and Yuan, 2001) and our own experiments (see Figs. 1 and 2) we decided to increase the efficiency of the skin-like region detection by combining the outputs of the thresholding operations in both color spaces using the following bounds

\[
\begin{align*}
&r \in [38, 55]; \\
g \in [25, 38]; \\
&H \in [0, 50] \cup [340, 360]; \\
&S \geq 0.2; \quad V \geq 0.35.
\end{align*}
\]

The efficiency of the proposed segmentation method was evaluated using various color images from the “Libor Spacek’s Collection of Facial Images” of the University of Essex, from the “AR Face Database” prepared by Aleix Martinez, from the “Psychological Image Collection at University of Stirling” and from the “Breakfast for Champions” image database. The new approach to skin segmentation proved to yield satisfactory results. This was also confirmed by tests performed on color images from a database of images corrupted by the red-eye artifact (see Fig. 3). This database consists of 250 true color images of different resolutions, obtained with different digital cameras under varying lighting conditions (Fig. 4).

Fig. 2. Distribution of the face skin color in the \( HSV \) space. Left column depicts patches of face regions taken from the database, to the right the three-dimensional distribution of the pixels is shown.
database was used to examine the efficiency of the proposed skin segmentation approach and to evaluate the effectiveness of the technique of redeye removal described in this paper.

It has to be stressed that the proposed method will work correctly with any reasonable skin detection method and that the efficiency of the skin detection module is not crucial in the new approach, as the detected skin regions are processed with morphological operators whose aim is to remove small skin-like regions and fill the holes in the facial image regions.

Fig. 5 illustrates the effectiveness of the thresholding operations in the rgb and HSV space, when
applying the bounds given in (7) and presents also the combined output obtained from both skin segmentation schemes.

In the experimentations, we observed that the thresholding in the $r, g$ space very often leads to false classifications of dark image regions. It is clearly visible in Fig. 5(c). However, when the output of the segmentation based on the $r, g$ space is combined with the result of the thresholding in the $HSV$ space, this effect is removed (Fig. 5(b)), which leads to better segmentation results.

2.2. Morphological cleaning process

The skin detection module classifies all skin tone regions as face candidate regions. This is often inaccurate and additional processing is needed to determine the actual face. To this end, morphological operators are applied to the identified skin tone regions in order to fill small holes and gaps in the face regions such as eyes, lips and nostrils, and also to remove small skin like areas which are unlikely to represent faces.

The cleaning stage uses the closing and opening operations, where closing is dilation followed by erosion and opening is erosion followed by dilation. The closing operation fills small gaps and merges close regions. The aim of the opening operation is to remove isolated, tiny objects which are unlikely to represent faces. The important parameter of the morphological operations is the size of the structuring element. In our system we used a square mask of $9 \times 9$ size and before the execution of the opening, closing operation we filtered the binary image with a $3 \times 3$ median filter. The results of the morphological cleaning process are shown in Figs. 6 and 16.

2.3. Gray-scale conversion

The third step of the correction of the redeye artifacts consists of finding image regions with
color features close to those, which represent the redeye effect. The aim of the conversion of the color image into its gray-scale representation is the enhancement of the image regions, which are likely to represent the redeye distortion.

In the literature and commercial applications, different approaches are applied to convert a color image into a monochrome one, in which the redeye is highlighted as a bright spot.

The gray-scale image can be obtained by calculating the colorimetric distance between a prototypical reference redeye chromaticity values and each image pixel contained in the region of interest (Hardeberg, 2001, 2002). The drawback of such an approach is that it is relatively time consuming and is not robust enough, as the color of the redeye is to large extent dependent on the subject and scene illumination.

Much more faster but not very effective as well, is the transformation from RGB to $YC_BC_R$ color space (Patti et al., 1998). The gray-scale conversion algorithm was based on the $YC_BC_R$ representation with gamma corrected ($\gamma = 3$) RGB values according to (Plataniotis and Venetsanopoulos, 2000)

$$F'_k = \begin{cases} 4.5F_k & \text{if } F_k \leq 0.018, \\ 1.09F_k^{1/\gamma} - 0.099 & \text{otherwise}, \end{cases}$$

where $F_k$ denotes the red, green and blue component ($k = R, G, B$).

$$\begin{bmatrix} Y \\ C_B \\ C_R \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112 \\ 112 & -93.786 & -18.214 \end{bmatrix} \begin{bmatrix} F'_1 \\ F'_2 \\ F'_3 \end{bmatrix}.$$  

Then the chrominance $C_r$ of the image is used as a basis for the redeye detection. Unfortunately such a simple scheme yields poor results and causes serious difficulties, when the segmentation of the redeye region is attempted (Fig. 7).

In this paper we introduce a heuristic method for the redeye region enhancement. As a result of
our experimentations three fast and efficient algorithms have been developed.

Below we present the operations which can be applied without any parameters or user intervention to perform the conversion from color to a single channel image.

Let us denote the pixel at position \((i,j)\) as \(F(i,j)\) and let the pixel consists of three RGB components: \(F(i,j) = \{R(i,j), G(i,j), B(i,j)\}\).

The output of the first operator \(T_1\) is the difference between the red channel component and the maximum of the green and blue channels

\[
T_1(i,j) = R(i,j) - \max \{G(i,j), B(i,j)\}. \quad (10)
\]

This simple operator detects efficiently the color image areas, where the red component dominates over the green and blue channels.

Fig. 6. Skin-like region detection and cleaning: (a) color test image, (b) result of skin-like region detection, (c) binary image representing skin-like regions, obtained after the morphological closing and opening operations, (d) the binary mask superimposed on the test image showing the skin-like areas.
The drawback of that algorithm is that its output is the same in the dark and bright image regions. If we perform the normalization with respect to the red component, we obtain

\[ T_2(i, j) = \frac{1}{R(i, j)} \times (R(i, j) - \max\{G(i, j), B(i, j)\}). \]  

(11)

The best results were achieved when combining the output of these operators. The formula used for the conversion of the color image into gray-scale representation is then

\[ T(i, j) = T_1(i, j) \cdot T_2(i, j) \]

\[ = \frac{[R(i, j) - \max\{G(i, j), B(i, j)\}]^2}{R(i, j)}. \]  

(12)
The efficiency of the new method of redeye enhancement and gray-scale conversion is presented in Fig. 8, where the outputs of $T_1$, $T_2$ and the final transformation $T$ is presented using a set of color test images. The same images were used to compare the efficiency of the new gray-scale conversion scheme with the results of previous approaches of Patti et al. (1998) and Hardeberg (2001, 2002). The results show that although the proposed method is very simply and fast, it outperforms the previously applied algorithms and allows more accurate pupil detection (Fig. 7).

Fig. 8. Efficiency of the applied redeye enhancement and gray-scale conversion algorithm: (a) red planes ($R$ of RGB) of the test images, (b) result of the $T_1$ transformation, (c) result of the $T_2$ transformation, (d) final result of the gray-scale conversion obtained as the combination of the $T_1$ and $T_2$ transformations.
2.4. Pupil detection

The next step of the algorithm is the detection of the image areas affected by the redeye effect. In the new approach, we assume that the redeye artifact is of approximately circular shape and we apply a fast edge detection technique based on a series of convolution masks depicted in Figs. 9 and 10. Our algorithm locates the redeye by detecting its edges, assuming the circular morphology of the pupil. To detect a circle of high intensity in the gray-scale image we apply matched filtering by convolution with a series of annular filters $M(r_k)$ of increasing radius $r_k$, ($k = 2, 3, \ldots, 25$). Fig. 9 shows an example of a convolution mask of radius 4 ($r_4$, mask size $11 \times 11$), whereas Fig. 10 depicts masks of larger radius.

Each filter responds to edges of a circle of radius $r_k$. We assume that the radius of the redeye is smaller than 25 pixels and assign to each gray-scale image pixel, the maximal output $M(r_k)$ of the edge detecting filter series.

The output of the edge detector is maximized when the filter mask is placed in the center of a circular pupil. However, in practice, the shape of the redeye can deviate much from the circular form and the final redeye region is formed as a union of disks of various radius.

In this way, after the automatic or manual thresholding, to the central pixels of the detected redeye region disks with radius $r_k$ corresponding to the highest output of the edge detection filter $M(r_k)$ are assigned and the redeye region is composed of a union of overlapping disks, as illustrated in Fig. 11.

The disk detection masks shown in Figs. 9 and 10 are very simple in order to minimize the computational load. In fact, regardless of the radius.

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**Fig. 9.** (a) Example of a convolution mask of radius 4 used for the detection of the redeye artifact. This mask can be applied as a difference of the convolution masks depicted in (b) and (c).

**Fig. 10.** Convolution masks for the pupil detection of radius 4, 6 and 8, (a, b and c respectively).
(mask size), the output is composed of 16 mask values only. We applied such a simple mask to avoid the need to use the discrete Fourier transform, however in the future work, we will apply more accurate masks based on a difference of Gaussians (DoG) and will perform the convolution in the frequency domain.

After the edge finding filtering has been applied, the output image has to be thresholded in order to find the binary mask, which assigns the value 1 to the detected redeye and 0 to the background and to perform the final task of redeye correction—red color replacement. The threshold parameter can be set experimentally by the operator to achieve the best possible visual appearance of the series of images to be corrected or can be evaluated automatically using some of the standard binarization methods. However, this is quite a difficult task since the image histogram is strongly unimodal. Nevertheless, we observed that good results have been achieved, when the threshold value was set to be equal to the mean value of the output pixels intensities. This approach was used for the quantitative evaluation of the efficiency of the proposed correction method.

Satisfactory results have also been obtained using a static threshold equal to 75% of the maximal output value of the edge detection filters (Fig. 12). This method already applied in (Czubin et al., 2002; Hardeberg, 2001, 2002) proved to give satisfactory results.

The dependence of the proposed method on the thresholding parameter is shown visually in Fig. 13, where different threshold values were applied. It is worth noticing that even if the threshold is significantly too small, good results can be obtained and the loss of the correction quality is in most cases not perceivable (Fig 13, middle column). However too large threshold values can produce a red ring around the corrected pupil (Fig 13, right column) which can lead to unacceptable image restoration.

2.5. Redeye color replacement

The last step of the redeye removal algorithm is the color replacement of the recognized artifact. Again the applied algorithm is very straightforward and fast. If a pixel has been detected as belonging to the redeye then it is replaced by an achromatic pixel with intensity mean $\{G, B\}$. This simple scheme proved to be very effective as the $G$ and $B$ color image components are not affected by the redeye effect and their mean value yields a natural appearance of the corrected pupils.

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Fig. 11. Illustration of the pupil finding algorithm: (a) red planes ($R$ of $RGB$) of the images affected by redeye, (b) output of the series of circular, edge finding masks, (c) images with superimposed detected redeye regions, (d) enlarged set of circles, the union of which produces the mask shown in (c).
3. Experimentation results

Some illustrative examples of the efficiency of the new technique are presented in Fig. 12, where the same set of images used in Figs. 7 and 8 was corrected. The performance of the described technique can also be evaluated visually in Figs. 14 and 15.

Fig. 12. Efficiency of the new method of redeye correction: (a) color test images of the eye region affected by the redeye distortion, (b) detected redeye regions, (c) final result of redeye localization and color replacement.
It has to be stressed that the skin detection step is important for the automatic redeye correction. It is clearly visible in Fig. 14, where the skin localization helps avoid the false correction of small reddish spots, which are outside of the skin regions. The same is valid for the Fig. 15, where without the skin detection step, many unnecessary corrections would be performed, which would result in changes of the color of regions marked with white in Fig. 15(b), which in turn would make the result of the correction process unacceptable.

However in some cases, false red spots can be found in the skin-like regions, which can result in misclassifications and false corrections as depicted in Fig. 14, where the candle lights were treated by the algorithm as redeyes or in Fig. 16, where false corrections were performed on the boy’s fingers. Sometimes, as in the case of Fig. 14, the false corrections are not perceivable and the whole correction process can be treated as successful, but in some cases, as in 16 the false corrections are quite visible, which causes that the manual region of interest selection has to be performed.

In order to evaluate quantitatively the proposed restoration scheme, we performed an automatic correction of a set of 250 color images affected with the redeye artifact, (a part of this database is shown in Fig. 4). This correction was made in a batch mode without any manual manipulation of the parameters.

We classified the corrected images into four groups. The first group consisted of images with all detected and corrected redeyes, without any false corrections. The second group consisted of images, in which all redeyes were detected and corrected, however in those images some false redeyes were corrected. The images with some not detected redeyes, but without false correction fell into the third class. The last group contains images with some not detected redeyes and false corrections.

Additionally each group of images was divided into two subgroups, to provide the information if the overall appearance of the image after the correction process was essentially improved (like in Fig. 14) or the method failed to increase the image quality (like in Fig. 16). The tests were performed by a team of three experts in digital photography in a laboratory with calibrated high quality monitors and supervised illumination conditions. The results of the visual quality assessment of the described method, based on a set of 250 images affected by the redeye effect are summarized in Table 1.

The results summarized in Table 1 indicate that the proposed here method performs well in the
majority of the tested cases. The new method’s failure rate was only 6.4% (16 out of 250 cases) and this in the automatic mode of operation. It is expected that that performance will improve significantly in the semi-automatic mode, in which the redeye regions can be selected manually by drawing a rectangle around a face with redeye effect.

Looking at the results depicted in Fig. 12, it is easy to observe that in some cases, when the pupil is partially covered by the eyelids, the amount of correction is sometimes too large. Although this effect is mostly not perceivable, it could be alleviated by additional examining of the color distribution of the detected redeye areas, in order to avoid cases when the eyelid color is falsely replaced with achromatic tone. This can be improved by many techniques. Preliminary research indicates that good results can be obtained using

Fig. 14. Efficiency of the new redeye correction algorithm: (a) result of the redeye detection when searching in the whole image, (b) result of the redeye detection in the skin-like regions only, (the detected spots, which are suspected to be redeyes are surrounded by circles, in order to better visualize the detection), (c) original test image, (d) corrected image with three falsely detected and corrected ‘redeyes’ (candle lights).
the active contours method (snakes), initialized in the centers of the detected redeye regions. Further, we intend to integrate a robust face algorithm (Hsuy et al., 2002), to increase the efficiency of the face detection module and to increase the performance of the automatic redeye correction.

We expect that the overall performance of the method would be increased if a robust face detection algorithm would be incorporated instead of the fast but rather simple skin detection scheme based on thresholding.

It is worth mentioning, that a robust and more complicated face detection module will increase the computational complexity of the overall scheme. The current system, mainly due to the computationally efficient skin detection scheme that it employs, is able to process 250 images of size 1280 × 960 in approximately 4 min using a 900 MHz desktop box.
4. Conclusions

In this paper an efficient redeye correction algorithm has been presented. The method can work in both an automatic or semi-automatic mode in which the user manually selects a region of interest. The method is fast, computationally inexpensive, reliable and it is able to locate redeyes in the facial areas under various degrees of illumination changes. Future work in this area will focus on integrating into the system a robust face recognition module based on active contours. It is antic-

![Fig. 16. Illustration of a case, in which our method failed to perform the correct redeye removal: (a) test image, (b) detected regions marked with green, (c) redeye correction result after the skin detection step; apart from the redeyes, 3 false spots have been detected in the skin region (depicted by red in the yellow area, representing the detected skin in (d) and their chrominance changed. As a result, the color of the fingertips was falsely changed.]

| Table 1 |
|------------------|------------------|------------------|------------------|------------------|
| Quality assessment | No misses, no false hits | No misses, false hits | Misses, no false hits | Misses, false hits |
| Success | 214 | 7 | 9 | 4 |
| Failure | 2 | 4 | 5 | 5 |

est.
ipated that the proposed scheme when completed will be used to restore amateur photographs and possibly will be incorporated directly into the digital camera acquisition system.

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