Pupil Localization by a Template Matching Method

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Abstract: In this paper, a new algorithm for pupil localization is proposed. The algorithm is based on a template matching approach; the original contribution is that the model of the pupil that is used is not fixed, but it is automatically constructed on the first frame of the video sequence to be examined. Therefore the model is adaptively tuned to each subject, in order to improve the robustness and the accuracy of the detection. The results show the effectiveness of the proposed algorithm.

1 INTRODUCTION

Among the different applications of biomedical image processing, e.g. Mitotic HEp-2 cells recognition (Percannella et al., 2011) or Blood Vessel Segmentation (Fraz et al., 2012), Eye Tracking plays an important role both from the research and commercial point of view. In fact Eye tracking is an important component in many applications including human computer interaction, virtual reality, and diagnosis of some health problems. Abnormal eye movements can be an indication of diseases such as balance disorders, strabismus, etc.

Several technologies have been used for eye tracking, such as electrooculography (EOG) or flying-spot lasers, but video-based eye tracking systems proved to be the most effective. In particular, head mounted eye tracking systems are more accurate than other kinds of video-based systems.

Detecting the pupil is the most frequently used method to track the horizontal and vertical eye position in video-based systems. If the detection can be done accurately and robustly, then the eye orientation can be determined from the pupil center coordinates. Unfortunately, significant errors in the pupil center computation may arise due to artifacts caused by eyelids, eyelashes, corneal reflections, make-up, etc.

Some attempts have been previously made to attain a fast and accurate pupil center detection; in the next section a brief survey on the subject is presented. A common limitation of these approaches is that they do not take into account the specificity of each observed eye, and so may fail when they encounter an eye with unusual characteristics (e.g. particularly large or small pupil, shape not exactly elliptical etc.) In this paper we propose a new, model-based, algorithm for pupil center localization, which adapts automatically to the characteristics of the observed pupil.

The remainder of the paper is organized as follows. In Section 2, we present some related works, while in Section 3 we describe the proposed pupil localization method. Section 4 show the results of the experimental phase and some conclusions are drawn in Section 5.

2 RELATED WORKS

In the literature on pupil detection, a first group of works (Boumbarov et al., 2009; Krishnamoorthy and Indradevi, 2010) is based on the technique of active contours. These methods assume that a parametric model of the shape of the contour of the pupil is known (usually an ellipse is used); then they employ different algorithms for the iterative learning of the chosen model parameters. Boumbarov et al. (Boumbarov et al., 2009) propose the use of a Particle Filter; the other approach works by minimizing an energy function based on the gradient (Krishnamoorthy and Indradevi, 2010).

A second group of works (Benletaief et al., 2010; Kinsman and Pelz, 2011) starts from a characterization of the pixels belonging to the pupil, and tries to reconstruct the pupil region from a seed point, by clustering adjacent pixels (Benletaief et al., 2010)

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or by using a probabilistic mixture model together with the Expectation-Maximization algorithm (Kinsman and Pelz, 2011).

Two other papers (S. Kim and Lee, 2011; Mohammadi and Raie, 2011) work with a RGB camera and first seek the iris contour, and then recognize the boundary of the pupil, either through geometrical properties (Mohammadi and Raie, 2011) or through the use of artificial neural networks (S. Kim and Lee, 2011).

Finally, a large group of papers (Kolodko et al., 2005; Yan et al., 2009) relies on the fact that the pupil localization systems typically use infrared (IR) cameras. In an IR image of the eye, the pupil is the darkest region in the image. Therefore these works binarize the initial image and perform a fitting of an ellipse (with a minimum and maximum size) on the binarized image contours. A variation of this scheme is presented in some papers, e.g. (Kocejko et al., 2008), which assume that the unique convex region resulting from binarization is the one corresponding to the pupil; then they identify the center of the pupil as the center of mass of the resulting region.

The methods of the first and second groups assume that a seed point belonging to the pupil can be easily and reliably found. The works that are based on image binarization make the hypothesis that there are no other elliptical regions in the image except the one corresponding to the pupil.

These assumptions may fail in many cases, due to the noise in the image, or because of the presence of other dark elements similar to the pupil color (such as the make-up), or due to non-perfect centering of the eye in front of the camera. Furthermore, all these methods cannot always recognize when the pupil is not present (closed eye) or if it is partially visible because of the eyelids.

The basic idea of our proposal, which overcomes the limits described above, is to build an appearance model of the pupil, which is specific to the eye under examination, and to search the portion of the image most similar to the model. The model is constructed (automatically) on the first frame of the sequence. The method makes no assumptions on the position of the pupil and therefore it is not based on an initial solution. Furthermore, by performing a global search, it is not deceived by regions that are circular but do not correspond to the pupil. Finally, by including a threshold on the similarity between model and image, it can recognize when the pupil is not present in the image.

3 THE PROPOSED METHOD

The main idea of the algorithm is to construct a model for the pupil on the first frame of the sequence, and then, for each succesive frame, to correlate the model with the image in order to find the image region that best matches with the model.

Given a template image of the pupil, for each frame, the steps of the algorithm are described in the following:

1. the image is thresholded with a fixed value (the illumination system is such that the pixels color of the pupil are always the darkest pixels in the image);
2. a template matching (Brunelli, 2009) is applied between the pupil model and the image in order to find the position of maximum correlation;
3. starting from this position, the algorithm performs a stabilization procedure in order to reduce the localization errors due to the noise in the image.

The correlation function used in the template matching is:

$$R(x,y) = \frac{\sum_{x',y'} (T(x',y') \cdot I(x+x',y+y'))}{\sqrt{\sum_{x',y'} (T(x',y')^2 \cdot \sum_{x',y'} I(x+x',y+y')^2}}$$

where T denotes the template and I denotes the image; the summation is done over template pixels $(x',y') \in T$.

Because of the noise and of the distortions along the edge of the region representing the pupil, the point of maximum correlation does not coincide exactly with the center of the pupil. For this reason a further step is performed to find a more stable pupil center.

Starting from the maximum correlation position, a contour finding algorithm is performed. Only the largest contour is considered, assuming that the smaller ones are due to noise. The found contour will include part of the contour of the pupil, but it may also include other borders (e.g. if the pupil is partially covered by the eyelid). Thus, an ellipse is fitted to the contour. The fitting is performed by calculating the ellipse that fits (in a least-squares sense) the set of 2D contour points. Finally, the center of the ellipse is taken as the pupil center.

Fig. 1 illustrates the steps described above: the template matching finds a first, not necessarily optimal, solution (Fig. 1a). Performing a search of the contours in the considered region, the largest contour corresponds to the pupil (Fig. 1b). Fig. 1c shows the ellipse found after the execution of an ellipse fitting algorithm, and Fig. 1d shows the new pupil center that significantly improves the solution found by the template matching alone.

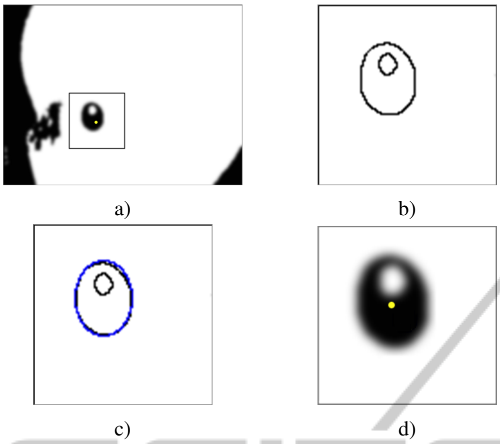


Figure 1: a) First solution after the application of the template matching. b) Contours finding on the considered region. c) Ellipse Fitting. d) Final solution.

The construction of the model of the pupil for the considered video sequence is carried out on the first frame, again with a method based on Template Matching. However, in this case we use a set of predefined templates. Starting from the point of maximum correlation, the actual region of the pupil is reconstructed through a Region Growing Process (Pratt, 2007) on the binarized image, by using as a seed point the solution resulting from Template Matching (See Fig. 2 for an example). Once this region is found, it is used as a template for subsequent frames.

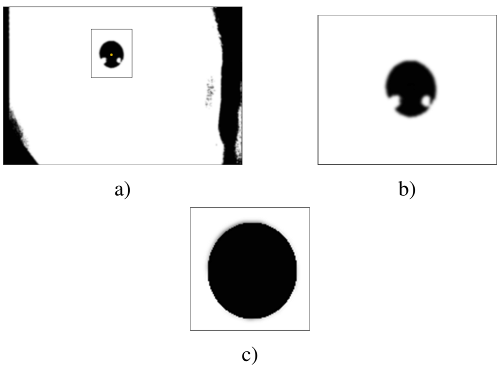


Figure 2: a) Template Matching Solution. b) Region Growing Result. c) Final Pupil Model.

4 RESULTS

A set of 28 videos (from 14 different subjects) was recorded to analyze the performance of the algorithm; the videos were acquired using an IR camera mounted on a mask worn by the subject. The average video length was 450 frames; therefore about 13000 frames were used in our experiments.

Of the 14 subjects, five were women, and four of them had make-up (eye-liner). In Fig. 3 some sample frames are shown.

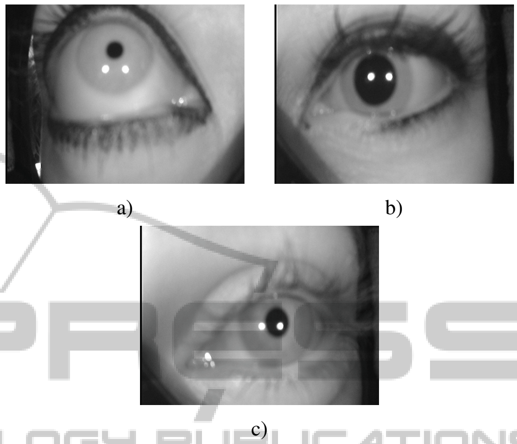


Figure 3: Samples frames from the acquired dataset.

The sequences ground truth (exact pupil position) for each frame of the video set has been manually detected and recorded in a file. The frames in which the eye was closed have been also noted in order to evaluate the ability of the algorithm in detecting the absence of a pupil in the image (because of the closing of the eyelid).

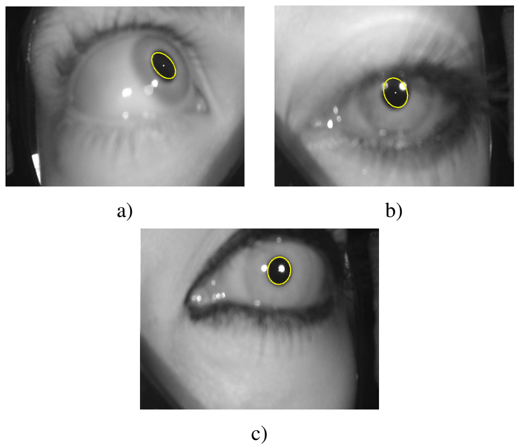


Figure 4: Samples frames in which the algorithm succeeds in detecting pupil center.

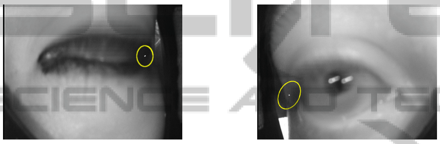
Pupil detection outcomes can be broadly classified into the following four possibilities:

- **True Positives.** The pupil has been detected correctly.

Table 1: Obtained results of the proposed algorithm.

# frames opened eyes	# frames closed eyes	TP	TN	FP	FN
13677	222	13062	152	568	130

- **True Negatives.** The algorithm identifies that there was no pupil to be detected, e.g. the eye closed.
- **False Positives.** The algorithm detects a pupil where there is none in the image, or the detected center is too distant (over a choosen threshold) from the real one.
- **False Negatives.** The algorithm detects that there is no pupil even though there is a clearly visible pupil in the image.



a) b)

Figure 5: Samples frames in which the algorithm fails in detecting pupil center.

Table 1 shows the incidence of such cases over the frames of the collected dataset. In 95% of the frames, the algorithm succeeds in detecting the pupil center or in detecting a closed eye.

In Fig. 4 it is possible to see three examples in which the algorithm succeeds in the detection of the pupil center. The cases are particularly difficult due to the large rotation of the eye (Fig. 4a) or because of very long eyebrows (Fig. 4b) or very pronounced makeup (Fig. 4c). Note also that because of the non perfect adherence of the mask to the face, dark and thick regions are present on the image borders: this causes, in many algorithms, a failure to find the correct position of the pupil.

In Fig. 5 there are two cases in which the algorithm fails: in the first case, due to the make-up, the algorithm fails to recognize the closed ey,e while in the second image, being very noisy, the shape of the pupil is very distorted.

5 CONCLUSIONS

In this paper a new model-based algorithm for pupil localization is presented. The algorithm overcomes some common problems affecting other approaches by constructing a model that is specific for the observed subject. The experimental results show the effectiveness of the proposed algorithm.

Future work will be oriented to the use of a more refined appearance model, incorporating probabilistic elements, in order to improve the detection accuracy for very noisy images and for the case in which the pupil is largely occluded by the eyelid.

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