Gradient flow based iris segmentation on noisy images

João C. Monteiro, Hélder P. Oliveira, Ana F. Sequeira, Jaime S. Cardoso

INESC TEC (formerly INESC Porto) and Faculdade de Engenharia, Universidade do Porto
{joao.carlos.monteiro,helder.oliveira,ana.filipa.sequeira}@fe.up.pt, jaime.cardoso@inescporto.pt

***Abstract*—The new challenges concerning iris recognition are based on the need to support less constrained image acquisition environments. The proposed algorithm aims to achieve robust iris segmentation, based on combined information from iris center and iris contour, with such images. A 5.72% mean error was obtained for the outer contour segmentation while the pupillary region presented a 9.36% mean pixel misclassification.**

I. Introduction

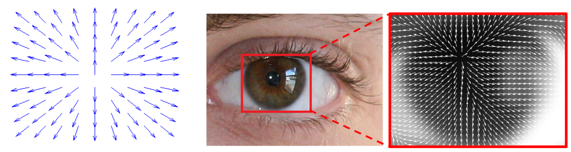
Presently, there are several biometric systems based on iris recognition with excellent rates of success [1], [2]. However, these results are due to the very constrained conditions under which iris data is acquired (infrared illumination of the eye, user collaboration, etc.). The new challenges for iris biometric systems arise when the attempt is made to perform iris recognition without user cooperation or under less ideal conditions (subject on the move, natural illumination, variable distance to the camera, etc.) [3]. In this work we used the mutual context of *limbic contour* and *iris center* in order to facilitate the recognition of each other. When performed independently, both tasks can be hard to perform since many other parts of the image may be falsely detected. However, these tasks can benefit from the context of each other.

II. Simultaneous detection of iris center and limbic contour

Researchers, from different type of areas, are now paying more attention to the context to aid visual recognition processes [4]. Central to the proposal in this work is the modelling of the mutual context of limbic contour and iris center, so that each can facilitate the recognition of the other. When performed independently, both tasks are nontrivial since many other parts of the image may be falsely detected. However, the two tasks can benefit greatly from serving as context for each other.

A. Algorithm description

Iris images present two very distinct regions: a high intensity region corresponding to the eye and the skin, and the iris region, at least *partially circular* and *lower in intensity*. Both sources of knowledge can be used separately but are intrinsically connected. The fact that the iris is a darker region against a brighter background translates into a specific divergent gradient orientation from its center, as well as a high gradient magnitude along its contour. The approach taken in this work was that of detecting pairs of iris center and limbic contour candidates that maximize a quality factor weighted by the afforementioned combined knowledge.



(a) (b)

Fig. 1. Gradient flow vector field: a) template and b) example iris image and c) respective gradient flow around iris center.

1) Iris center detection: Iris center candidates are detected using a template matching step between the gradient orientation of an iris image, exemplified in Fig. 1(b), and the template presented in Fig. 1(a). The template matching is performed by computing the cross-correlation,c_{corr}, between the afforementioned vector fields, with $c_{corr}{=}(f * g)[n] \overset{def}{=} \sum f^*[m]g[n{+}m]$. The center candidates are the local maxima of cross-correlation above a certain threshold, manually tuned to $t = 0.85$.

2) Limbic contour detection: For limbic boundary detection the image grid is considered as a graph with pixels as nodes and edges connecting neighbouring pixels. Each iris center candidate is associated with an optimal limbic contour candidate, using a shortest path algorithm. A window centered in the iris center candidate is converted to polar coordinates. The limbic contour is then represented by a curve between the left and right sides of the image. The shortest path algorithm is used between each point in the left side of the image and the whole right side, and vice-versa. The result of such operations is the convergence of all the paths to a set of N points. Each of these convergence points yields a closed contour candidate.

3) Best contour choice: From the previously described steps a set of center/contour candidate pairs (Cp) is built. The discrimination between these candidates is performed by computing a quality factor, Q, for each pair, and then choosing the highest. The quality factor is given by $Q(Cp) = \frac{\mu(\Delta C)\cdot\rho_p}{(1-S(C))}$, where $\mu(\Delta C)$ is the mean gradient alongside the contour, ρ_p

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(a) (b) (c) (d)

Fig. 2. Examples of results of the proposed algorithm (Cyan) against the manually annotated contours (Yellow).

is the cross-correlation of the center candidate, and S is the shape factor of the contour (with perimeter P and area A), given by $S(C) = \frac{P^2}{4\pi \cdot A}$.

B. Pupil probability estimation

For iris recognition the limbic contour represents only part of the segmentation information. To isolate the iris region it is also necessary to detect the inner contour between the pupil and the iris, known as the pupillary contour. As many times this contour is weakly contrasted against the pupil, subtraction of the red and blue colour channels was used. Using the previous center as a start point the image is converted to the polar domain and the circle that best fits the shortest path is computed as a high probability pupillary region.

III. Results

A. Image dataset

To evaluate the proposed algorithm the UBIRISv2 database was chosen [5]. This choice was made due to UBIRIS' wide variety of noise factors (reflections, occlusions, pigmentation, etc.). A dataset composed by 100 randomly selected images from 20 distinct individuals was created. All 100 images were manually annotated for both the limbic and pupillary contours so as to allow the evaluation of the obtained results.

B. Iris center and limbic contour

The limbic contour segmentation was evaluated using the mean and maximum/Hausdorff distance between the manually annotated and detected contours, for five distinct colour channels: RGB (red, green and blue), intensity from HSI and PCA (optimal separation) of the RGB channels. The main results are summarized in Table I and some exemplifying images are presented in Fig. 2. A significant improvement in the detected center error was noted, when using the centroid of the detected limbic contour (NCE), instead of the local maxima of the cross-correlation image. The use of combined information resulted in a zero misdetection ratio of the correct center/contour pair. All channels except PCA presented similar good results of approximately 6% mean error and 15% maximum error.

C. Pupillary probability region

The pupillary region errors were measured as the percentage of iris points falsely classified as pupil (NP) and the percentage of pupil points falsely classified as iris (NI). With the proposed algorithm values of $NP = 8.06\%$ and $FN = 1.30\%$ were obtained. Once again the iris center error after the pupillary region is defined (PCE) is lower (5.02%) when compared to both CE and NCE.

TABLE I
Main results obtained with the proposed algorithm: center error of the chosen center from cross-correlation, center error of the centroid of the detected limbic contour, mean and maximum error of the detectedd limbic contour. All values are in percentage with respect to the mean radius of the iris.

	Blue	**Red**	**Green**	**PCA**	**Intensity**
Center	14.56	10.72	12.89	13.06	11.94
Centroid	5.80	5.26	5.82	13.07	5.31
Mean	5.72	5.78	5.97	9.02	5.76
Hausdorff	14.64	14.74	14.84	19.66	14.69

IV. Conclusion

With new challenges rising in the iris recognition field, in order to deal with non-ideal images, the development of new improved systems is gaining renewed interest. In this work an iris segmentation algorithm for images acquired under unconstrained conditions was proposed with some good preliminary results. Some improvements in future work will be related with eyelid detection to lower limbic contour error and generalization to non-circular pupillary regions.

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