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Improving colour iris segmentation using a model selection technique ☆

Yang Hu*, Konstantinos Sirlantzis, Gareth Howells

School of Engineering and Digital Arts, Jennison Building, University of Kent, Canterbuty CT2 7NT, UK

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ABSTRACT

In this paper, we propose a novel method to improve the reliability and accuracy of colour iris segmentation for captures both from static and mobile devices. Our method is a fusion strategy based on selection among the segmentation outcomes of different segmentation methods or models. First, we present and analyse an iris segmentation framework which uses three different models to show that improvements can be obtained by selection among the outcomes generated by the three models. Then, we introduce a model selection method which defines the optimal segmentation based on a ring-shaped region around the outer segmentation boundary identified by each model. We use the histogram of oriented gradients (HOG) as features extracted from the ring-shaped region, and train a SVM-based classifier which provides the selection decision. Experiments on colour iris datasets, captured by mobile devices and static camera, show that the proposed method achieves an improved performance compared to the individual iris segmentation models and existing algorithms.

1. Introduction

Iris recognition has been one of the most reliable techniques for biometric authentication due to the inherent stability, randomness and high degree of freedom of iris pattern. As a fundamental step of iris recognition, iris segmentation is an important prerequisite for iris recognition systems. The pioneering work by Daugman [1] shows the effectiveness of an integro-differential operator for near-infrared (NIR) iris images captured in controlled environment. Following Daugman, a number of iris segmentation algorithms [2–7] have been proposed.

Despite excellent performance, the aforementioned algorithms are difficult to be deployed on mobile devices, such as smart phones, tablets and pads. The reason is that these algorithms are less effective for colour iris images captured by mobile devices. Compared with NIR images, colour iris images are much noisier due to specular reflection. Additionally, mobile devices usually work in less constraint environment, which leads to more noise factors such as illumination variance, eyelids occlusion and motion blur. Therefore, it is necessary to investigate an effective colour iris segmentation method.

Over the last few years, significant research has been focusing on colour iris segmentation. Many colour iris segmentation methods have been proposed. For example, intergro-differential constellation algorithm [8], intergro-differential operator in YIQ colour space [9], knowledge-based algorithm [10], improved Hough transform [11], grow cut based algorithm [12], classifier based methods [13,14]. These algorithms report excellent performance. However, the test datasets used to evaluate these algorithms are captured by static cameras. The performance of these algorithms on mobile data is unknown.

To evaluate and develop algorithms for colour iris images captured by mobile devices, Marsico et al. build a dataset of mobile iris images, MICHE [15]. MICHE consists of more than 2500 colour images mainly captured by iPhone5 and Samsung Galaxy S4. Meanwhile, a mobile iris challenge evaluation (MICHE) has been organized to promote researches on mobile data. In this paper, we investigate colour iris segmentation using the mobile data in MICHE dataset. We propose a model selection method to enhance the stability and accuracy of our colour iris segmentation algorithm. The flowchart of the proposed model selection method is shown in Fig. 1. Firstly, for the input iris image, we obtain multiple segmentations using multiple segmentation models. Then, we define a ring-shaped region around the outer segmentation boundary and use this to evaluate the quality of segmentations produced by each one of the models. The histogram of oriented gradients (HOG) [16] is extracted from this ring-shaped region as feature vector. Finally, we train a classifier using the HOG features, and use the classification decision to select the optimal segmentation in the test phase.

Contributions. Our contribution are summarised as follows. First, we analyse three colour iris segmentation models (one circle model and two ellipse models) to show that model selection is able to

☆ This paper has been recommended for acceptance by Maria De Marsico.
* Corresponding author. Tel.: +44 1227 824412; fax: +44 1227 456084.
E-mail address: yh94@kent.ac.uk (Y. Hu).

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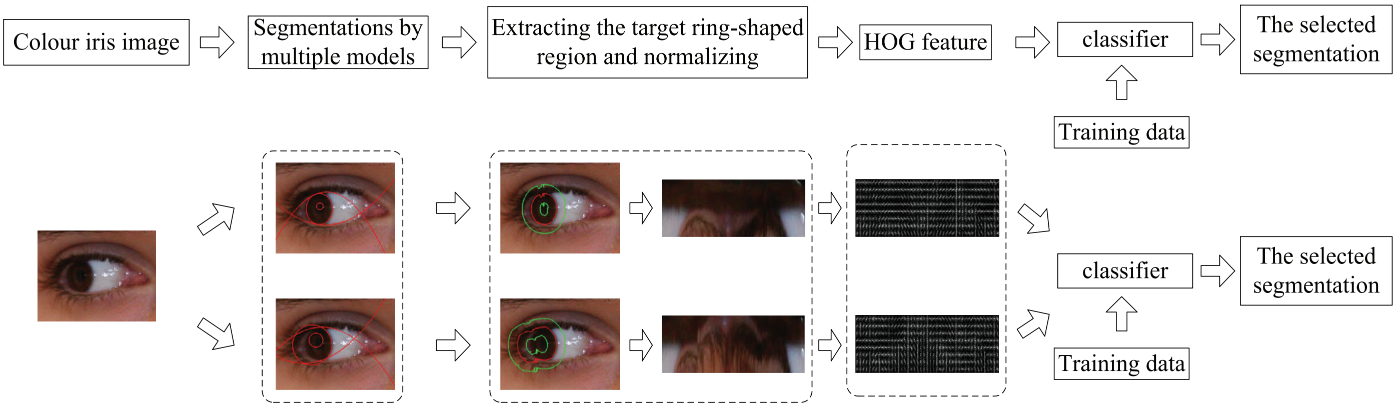

Fig. 1. The flowchart of the proposed algorithm. For the input colour iris image, we firstly segment the iris boundaries using multiple iris segmentation models. Then, we focus on a ring-shaped region (between the two green curves in the images of the third step) around the outer segmentation boundary (the red curve in the images of the third step). This ring-shaped region is normalized and HOG features are extracted from the normalized image. Finally, a pre-trained classifier is used to select the best segmentation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

improve the performance of colour iris segmentation. Second, we propose an effective model selection method to identify the optimal segmentation. We introduce a ring-shaped region around the outer segmentation boundary, and we show that HOG are effective features to distinguish between good and poor segmentations. Finally, we study experimentally the performance of the proposed algorithm on images captured by both mobile device and static camera.

The rest of the paper is organized as follows. Section 2 describes and analyses the three iris segmentation models. Section 3 presents the proposed method for model selection. Section 4 reports the experimental results on colour iris datasets. Finally in Section 5, we conclude the paper.

2. Iris segmentation models and analysis

In this section, we give an iris segmentation algorithm consisting of three iris segmentation models: one circle model and two ellipse models. The algorithm may be divided into the following steps: coarse iris localization, limbic boundary segmentation, pupillary boundary segmentation, eyelids fitting, shadow and reflection removal. Furthermore, we use synthetic data to study the characteristics of the three models and demonstrate that a model selection is able to improve the performance over each individual model.

2.1. Coarse iris localization

We propose to locate the iris region by a coarse iris map based on the correlation histogram of super-pixels [17]. We operate on red channel, since the observation in Ref. [18] suggests that red channel is the most informative for colour iris images.

As a pre-processing step, we perform contrast adjustment to make iris region more distinguishable. On the normalized red channel, pixels whose intensity value lies between a low threshold and a high threshold are mapped to $[0, 1]$, and the remaining pixels are clipped. Let m_r be the mean intensity value of the normalized red channel. We set the low threshold to $m_r - \sigma$ and set the high threshold to $m_r + \sigma$, where σ is a parameter set to 0.2 experimentally (in this paper, all parameters for iris segmentation are tuned based on a 500-image subset of UBIRIS V2 dataset [19]; this subset was released for NICE I contest [20]).

To illustrate the effect of contract adjustment, we present some example results of coarse iris localization with and without contrast adjustment in Fig. 2(b) and (c), respectively. It can be seen that with contrast adjustment, the coarse iris region is more distinguishable and consistent.

We compute super-pixels after contrast adjustment. Super-pixels are essentially the over-segmentation of an image. It is perceptually meaningful because it preserves local structure of an image. An example of super-pixel is shown in Fig. 2(a). In this paper, we employ the simple linear iterative clustering (SLIC) algorithm [17] to compute super-pixels.

We use correlation histogram (CH) as a feature to distinguish between iris and non-iris super-pixels. Denote the total number of super-pixels in the contrast-adjusted red channel by n, the CH of each super-pixel consists of $n - 1$ bins. For the ith super-pixel, we firstly calculate a n-bin histogram $\boldsymbol{C}^i$, with the jth bin, denoted by C_j^i, calculated as:

$$C_j^i = \frac{\langle \boldsymbol{h}_i, \boldsymbol{h}_j \rangle}{\sum_{j=1, j \neq i}^{j=n} \langle \boldsymbol{h}_i, \boldsymbol{h}_j \rangle} \tag{1}$$

where $\boldsymbol{h}_i$ and $\boldsymbol{h}_j$ denote respectively the normalized histogram of the ith and jth super-pixel, and $\langle \bullet, \bullet \rangle$ calculates the inner product of two vectors. The CH is obtained by removing the ith bin of $\boldsymbol{C}^i$. The reason of the removing is that the ith bin of $\boldsymbol{C}^i$ reveals the self similarity of the ith super-pixel and it is less informative for our aim.

The intuition behind CH is that the iris region is visually more unique in an iris image. As a result, the CH of iris super-pixels has few peaks, since few super-pixels are similar with iris super-pixels. In contrast, the CH of non-iris super-pixels tends to distribute across most of the bins due to a broad similarity.

We use entropy to distinguish between the CH of iris and non-iris super-pixels. Let E^i be the entropy of the CH of the ith super-pixel, E^i is calculated by:

$$E^i = -\sum_{j=1}^{n-1} C_j^i \log_2 C_j^i \tag{2}$$

An iris super-pixel tends to have a lower entropy value, because its CH concentrates on few bins. In contrast, a non-iris super-pixel corresponds to higher entropy value due to the broad distribution of its CH. To highlight iris region and build the coarse iris map, we fill each super-pixel with an intensity based on the entropy of CH. Let S^i be the intensity of the ith super-pixel, we calculate S^i by:

$$S^i = e^{-E^i} \tag{3}$$

The examples of coarse iris maps are shown in Fig. 2(b). We call it a 'coarse' map because it is not very accurate—it can be seen that some other parts of the image such as the eyelids and eyebrows are also highlighted. The reason is that these parts also show some uniqueness in iris images. However, coarse iris map helps us roughly locate iris