Pattern Recognition Letters 91 (2017) 44–51

Contents lists available at ScienceDirect

Pattern Recognition Letters

journal homepage: www.elsevier.com/locate/patrec

FIRE: Fast Iris REcognition on mobile phones by combining colour and texture features

Chiara Galdi*, Jean-Luc Dugelay

EURECOM, Campus SophiaTech, 450 Route des Chappes, CS 50193 06904 Biot Sophia Antipolis cedex, France

ARTICLE INFO

Article history:
Available online 1 February 2017

MSC:
41A05
41A10
65D05
65D17

Keywords:
Noisy iris recognition
Fast iris recognition
Multi-classifier
Visible light
MICHE DB
MICHE II

ABSTRACT

FIRE is a Fast Iris REcognition algorithm especially designed for iris recognition on mobile phones under visible-light. It is based on the combination of three classifiers exploiting the iris colour and texture information. Its limited computational time makes FIRE particularly suitable for fast user verification on mobile devices. The high parallelism of the code allows its use also on large databases. FIRE, in its first version, was submitted to the Mobile Iris CHallenge Evaluation part II held in 2016. In this paper, FIRE is further improved: a number of different techniques has been analyzed and the best performing ones have been selected for fusion at score level. Performance are assessed in terms of Recognition Rate (RR), Area Under Receiver Operating Characteristic Curve (AUC), and Equal Error Rate (EER).

1. Introduction

The need of secure use of data and services joined to the ever-increasing technological development of the imaging sensors led to the spread of biometric recognition systems on new devices. Mobile phones have the main advantage of being portable, ever more computationally powerful, and equipped with high resolution cameras. Providing a secure and accurate way to get authenticated at any moment and from any place is of utmost interest nowadays. However, there are a number of issues related to iris recognition on mobile devices, originating from the fact that the acquisition of the iris image is performed in unconstrained settings, such as out-of-focus images, specular or diffuse reflections, eyelid or eyelash occlusions, low resolution images, etc. [8,18]. This kind of images are called "noisy", and require ad hoc solutions e.g. segmentation algorithm and feature extractor, particularly designed for "noisy iris recognition".

A novel technique for noisy iris segmentation exploiting the Watershed transform has been presented in [1], while a solution for secure home banking based on user iris verification using a mobile device, i.e. a tablet, is presented in [7]. In [3], a novel approach based on the use of spatial histograms is presented. Other biometric traits has been also exploited for user recognition on mobile devices, including ear recognition in [10], gait in [15], keystroke and finger pressure in [21], arm movement when answering or placing a call in [5], speech, alone or in combination with other biometrics, in [14] and [17], and 3d face recognition in [19].

An important aspect of the proposed approach, is its suitability for iris recognition under visible light, taking into consideration the fact that there are many application scenarios in which Near Infra Red (NIR) illumination is not available or applicable. For example for continuous re-identification, i.e. when the system continuously verifies the user identity, in which case the user cannot be constantly exposed to NIR light, since the effects of a prolonged exposure to NIR light are still uncertain. Another example scenario in which NIR illumination cannot be available is for forensic, i.e. the process of analyzing images or videos from different sources to off-line verification of the identity of a person.

In this paper, we present FIRE, a novel approach for iris recognition particularly designed for iris recognition on smartphones and presented in its first version in [11] for the MICHE II - Mobile Iris CHallenge Evaluation Part II, held in 2016[1] in conjunction with the International Conference on Patter Recognition - ICPR 2016. The algorithm is based on the combination of three feature extractors,

* Corresponding author.
E-mail address: chiara.galdi@eurecom.fr (C. Galdi).

[1] http://biplab.unisa.it/MICHE_Contest_ICPR2016/index.php.

http://dx.doi.org/10.1016/j.patrec.2017.01.023

each of which describes a different characteristic of the iris: an iris colour descriptor, an iris texture descriptor, and an iris colour spot (hereinafter "cluster") descriptor. FIRE is tested on the MICHE-I[2], an iris image database collected with different mobile devices [9].

The key features of the proposed method are: (i) the use of the colour information (only available when using visible light illumination), (ii) the suitability for noisy iris recognition, (iii) the limited computational time, and (iv) the high parallelization of the code.

In this paper we present the new experiments carried out, consisting in testing different techniques for the colour and texture feature extraction, and the corresponding evaluation in terms of Recognition Rate (RR), Area Under Receiver Operating Characteristic Curve (AUC), and Equal Error Rate (EER).

The remainder of the paper is organized as follows: in Section 2, the multi-classifier algorithm is described; in Section 3 the experimental setting is described in order to assure experiment reproducibility. In Section 4 the experimental results are presented and Section 5 concludes the paper.

2. Colour and texture feature based multi-classifier

The iris presents a complex pattern made up of many distinctive features such as arching ligaments, furrows, ridges, crypts, rings, corona, freckles, and a zigzag collarette [6], some of which may be seen in Fig. 2 (left). However, in order to capture these minute characteristics, it is necessary to have a high quality imaging sensor, adequate lighting conditions, a small distance between the eye and the sensor.

For the design of the proposed approach, we focused on those characteristics that are more likely to be observable on iris images captured under visible light and by mobile devices, see Fig. 2 (right). We analyzed the images collected in the MICHE-I database and observed that: colour is for sure a discriminative feature, even if not sufficient to uniquely distinguish an individual; in these kind of images, the texture is less clear compared to NIR iris images; some macro-features easily detectable on noisy images, such as colour spots (see Fig. 4 as reference) can help in the recognition process.

The proposed solution is a multi-classifier approach, combining features of different nature in order to maximize the performances by exploiting as much as possible the information that is possible to retrieve from noisy iris images. FIRE is made up of three descriptors, namely the colour descriptor, the texture descriptor and the cluster descriptor. In Fig. 1, a flow chart describing the proposed approach is given.

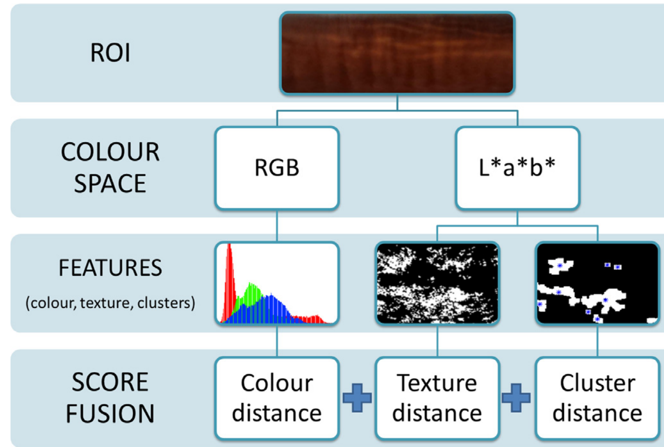

Fig. 1. Algorithm flow chart.

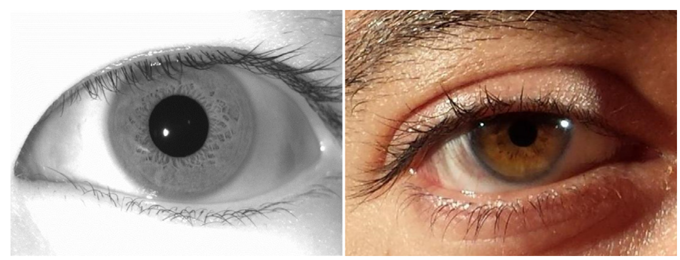

Fig. 2. Examples of iris acquisition, under near infra red illumination (left, from the Gender From Iris (GFI) Dataset, [24]) and under visible light (right).

2.1. Colour descriptor

Iris image databases can be distinguished in two main categories, those acquired under Near Infra Red (NIR) illumination and those captured under Visible Light (VL). NIR databases are composed by grey scale images, see Fig. 2 as reference. The MICHE-I database, on which the MICHE II participants were asked to test their approaches, has been acquired under VL. Thus, the colour information can be exploited to improve the recognition performances. A number of colour metrics have been tested and are described in the following. These metrics are mostly used for image retrieval [25]. A MATLAB implementation by Boris Schauerte[3] of the colour distances presented in [20], has been employed.

Given two irises, each picture is first split in small blocks and for each pair of corresponding blocks, the colour distance is computed. The minimum colour distance obtained is the final score returned by the colour descriptor.

Hereinafter, we adopt the mathematical notation proposed in [20], where an histogram $H = \{h_i\}$ is a mapping from a set of d-dimensional integer vectors i to the set of nonnegative reals. These vectors typically represent bins. For instance, in a grey-level histogram, d is equal to one, the set of possible grey values is split into N intervals, and h_i is the number of pixels in an image that have a grey value in the interval indexed by i (a scalar in this case).

2.1.1. Colour histogram distance

The first colour descriptor is based on a technique designed for image retrieval in image databases. The Euclidean distance between the colour histograms of the two images to be compared is computed as follows:

$$d_E(H, K) = \sqrt{\sum_i (h_i - k_i)^2}$$

where $H = \{h_i\}$ and $K = \{k_i\}$ represent the two colour histograms. This technique is fast but its major drawback is that it accounts only the dissimilarity between corresponding bins, and do not use information across bins. Two different bins may represent perceptually similar colours but are not compared crosswise. All bins contribute equally to the distance [13].

2.1.2. Chi-square distance

The chi-square histogram distance comes from the chi-square statistics to test the fit between the distribution and observed frequencies [2]. In histograms, the difference between large bins is less important than the difference between small bins and that should be reduced. The chi-square histograms take this into account [16].

The chi-square statistics is defined as follows:

$$d_{\chi^2}(H, K) = \sum_i \frac{(h_i - m_i)^2}{m_i}$$

[2] http://biplab.unisa.it/MICHE/database/.
[3] http://schauerte.me/.