Pattern Recognition 69 (2017) 199–212

Contents lists available at ScienceDirect

Pattern Recognition

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

Towards contactless palmprint recognition: A novel device, a new benchmark, and a collaborative representation based identification approach

Lin Zhang[a,b,*], Lida Li[a], Anqi Yang[a], Ying Shen[a], Meng Yang[c]

[a] School of Software Engineering, Tongji University, China
[b] Collaborative Innovation Center of Intelligent New Energy Vehicle, Tongji University, China
[c] School of Computer Science and Software Engineering, Shenzhen University, China

ARTICLE INFO

Article history:
Received 5 October 2016
Revised 10 March 2017
Accepted 15 April 2017
Available online 19 April 2017

Keywords:
Contactless palmprint recognition
Collaborative representation
Block-wise features
Image quality assessment

ABSTRACT

Biometric authentication has been found to be an effective method for recognizing a person's identity with a high confidence. In this field, the use of palmprint represents a recent trend. To make the palmprint-based recognition systems more user-friendly and sanitary, researchers have been investigating how to design such systems in a contactless manner. Though substantial effort has been devoted to this area, it is still not quite clear about the discriminant power of the contactless palmprint, mainly owing to lack of a public, large-scale, and high-quality benchmark dataset collected using a well-designed device. As an attempt to fill this gap, we have at first developed a highly user-friendly device for capturing high-quality contactless palmprint images. Then, with the developed device, a large-scale palmprint image dataset is established, comprising 12,000 images collected from 600 different palms in two separate sessions. To the best of our knowledge, it is the largest contactless palmprint image benchmark dataset ever collected. Besides, for the first time, the quality of collected images is analyzed using modern image quality assessment metrics. Furthermore, for contactless palmprint identification, we have proposed a novel approach, namely CR_CompCode, which can achieve high recognition accuracy while having an extremely low computational complexity. To make the results fully reproducible, the collected dataset and the related source codes are publicly available at http://sse.tongji.edu.cn/linzhang/contactlesspalm/index.htm.

1. Introduction

The need for reliable user authentication techniques has significantly increased in the wake of heightened concerns about security in networking, communication, and mobility [1]. Bolstered by the requirements of numerous applications, such as access control, aviation security, and e-banking, automatically recognizing the identity of a person with high confidence has become a topic of intense study. To address such an issue, biometric-based methods, which use unique physical or behavioral characteristics of human beings, have recently been drawing increasing attention because of their high accuracy and robustness. Actually, in the past decades or so, researchers have exhaustively investigated a number of different biometric identifiers, such as fingerprints [2,3], faces [4–7], irises [8–11], palmprints [12–16], hand geometry [17], finger-knuckle-print [18–20], ear [21], etc.

Among the many biometric identifiers, the palmprint has recently received significant attention due to its non-intrusiveness and ease of data collection. Palmprint refers to the skin patterns on the inner palm surface, comprising mainly two kinds of features, the palmar friction ridges (the ridge and valley structures like the fingerprint) and the palmar flexion creases (discontinuities in the epidermal ridge patterns) [13]. As an important member of the biometrics family, the palmprint is appealing and has various of desired properties, such as high distinctiveness, robustness, and high user-friendliness, etc. Actually, the use of palmprints for personal authentication can trace back to Chinese deeds of sale in the 16th century [22].

The first automated palmprint identification system became available in the early 1950s [13]. Since then, researchers have devoted a great deal of efforts in improving the effectiveness and efficiency of palmprint recognition systems. Currently, most devices for capturing palmprint images are contact-based (for example, the 2D palmprint acquisition device proposed in [12] and the 3D

* Corresponding author at: School of Software Engineering, Tongji University, China.
E-mail address: cslinzhang@tongji.edu.cn (L. Zhang).

http://dx.doi.org/10.1016/j.patcog.2017.04.016

palmprint acquisition device proposed in [16]), which implies that the user needs to touch the device when his/her palmprint images are collected. When capturing palmprint images with contact-based devices, users are asked to put their hands on a planar surface and/or have fingers restricted by pegs. Obviously, such devices have their inherent drawbacks. At first, they are not user-friendly since the pose of user's hand needs to be strictly constrained when the image is captured [23]. Elderly or people with arthritis or other diseases that limit dexterity may have difficulty placing their hands on a flat surface (even guided by pegs) [24]. Secondly, the palmprint remains left by former users on the sensor's surface will possibly affect the image content or image quality of later users. That will probably decrease the system's accuracy. Moreover, those remained prints could be copied for illegitimate purposes [24,25]. Thirdly, when such a device is deployed in a case with a large number of users, it will raise hygienic concerns; people are concerned about placing their fingers or hands on the same sensor where countless others have also placed theirs [23,25]. Considering these shortcomings, recently, researchers have begun investigating how to build palmprint recognition systems in a contactless manner, which is also our focus in this paper.

The remainder of this paper is organized as follows. Section 2 introduces related work and our contributions. Section 3 introduces our newly designed contactless palmprint acquisition device. Our ROI extraction scheme is presented in Section 4. Section 5 presents our novel approach for contactless palmprint identification. Section 6 presents our newly established benchmark dataset and reports the experimental results. Finally, Section 7 concludes the paper.

2. Related work and our contributions

In this section, we will at first review some representative work in the field of contactless palmprint recognition from three aspects, the equipments designed for capturing contactless palmprint images, the collected benchmark datasets, and the matching methods. It needs to be noted that strictly speaking, the mobile palmprint recognition (i.e., performing palmprint recognition on mobile phones) also belongs to the field of contactless palmprint recognition. However, since that field has its own inherent characteristics and needs to be separately investigated, it will not be discussed in this paper.

2.1. Contactless palmprint acquisition devices

In [26], Chen et al. adopted a digital camera to acquire palmprint images against a dark background. In their system, two 3U 23-watt lights were used to provide illumination and were arranged in appropriate positions. Chen et al.'s setup is shown in Fig. 1(a), from which it can be seen that various hardware parts were not integrated into a complete usable system. In addition, with such a system, images can only be manually captured. Consequently, Chen et al.'s system can only be used in lab.

In Kumar's palmprint acquisition device [27], the camera, the lens, and the fluorescent light source are enclosed in a semi-closed box. For sample acquisition, the user can put his/her hand into the box inside, and then the palmprint image can be captured against a dark background (the top cover of the box). We cannot get any further information about this device since the author did not provide drawings or photos of its internal structure. From sample images captured, it can be seen that in Kumar's device [27] the free space left for the hand in the box is quite limited and thus it is highly likely that the user's fingers may touch the walls of the box. So, it may raise users' hygienic concerns. In Fig. 1(b), a sample image collected by Kumar's device is shown.

In [28], Hao et al. built a multispectral contactless palmprint recognition system, whose design is shown in Fig. 1(c). With Hao et al.'s system, when sample images are being captured, 6 groups of LEDs ranging from violet to near infrared (IR) will be switched on sequentially, and thus 6 images under different lighting conditions can be collected. It is easy to know that the data acquisition using such a device is quite time-consuming.

In [25,29], Michael et al. built a low-cost contactless palmprint acquisition device as shown in Fig. 1(d). A 1.3 mega pixel web camera and a 9W white light bulb are mounted inside a semi-closed box. As shown in Fig. 1(d), there is no top cover with Michael et al.'s device, which may cause two problems. At first, since the distance between the user's palm and the camera cannot be restricted, the quality of collected images may vary much. Secondly, when it works, its intense light may directly enter into the user's eyes, which will inevitably make the user uncomfortable. Therefore, this prototype system is maybe difficult to be commercialized.

In [30], Poinsot et al. collected palmprint images using a Logitech QuickCam Pro 9000 webcam against a green background. Neither a housing nor additional lights are used in their setup. Images are captured under natural illumination. One sample image collected by Poinsot et al. is shown in Fig. 1(e). Obviously, such a system cannot be used in practical security-critical applications.

In [31], Ferrer et al. proposed a bi-spectral contactless hand based biometric system, which could capture palm images under visible and IR lighting conditions simultaneously. The IR image is mainly used to facilitate the segmentation of the visible image. As shown in Fig. 1(f), Ferrer et al.'s device has no housing so it has similar potential problems as Michael et al.'s [25,29].

In order to study multi-sampling hand recognition, Morales et al. constructed a contactless palmprint acquisition device [32] as shown in Fig. 1(g). The design principle of this system is inspired by credit card readers. As shown in Fig. 1(g), two plates delimit the area through which the user passes his/her hand with a vertical movement. During the transit of the hand between two plates, sample images can be captured. With respect to the camera, Morales et al. adopted a Logitech C600 webcam.

Quite recently, Aykut and Ekinci developed a prototype system for contactless palmprint authentication [33], as shown in Fig. 1(h). Their capturing device is a low-cost CCD camera with a DC-auto iris lens. Using such a device, the distance between the user's hand and the camera cannot be restricted, so some captured images may be out of focus. In addition, since there are no back and forth walls of the device's housing, the LED light may hurt the user's eyes.

Main features and potential shortcomings of the existing contactless palmprint acquisition devices abovementioned are summarized in Table 1, following a chronological order. Having identified the disadvantages of the existing devices, it motivates us to design a novel one with the following characteristics. (1) All the hardware parts are enclosed in a housing. (2) The light source cannot hurt the user's eyes. (3) Enough space is reserved for the user to move his/her hand freely. (4) The distance between the camera and the user's hand is constrained to make sure the palm is within the camera's depth of field. (5) The collected image can have a simple dark background. Details of our novel contactless palmprint acquisition device can be found in Section 3.

2.2. Benchmark datasets publicly available

With the developed devices, some researchers have collected benchmark contactless palmprint datasets and made them publicly available.

In [28], Hao et al. collected a multispectral palm image dataset (CASIA dataset [34]). Images were taken from 200 hands in 2 separate sessions. In each session, there were 3 samples. Each