Door Knob Hand Recognition System

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Abstract

Biometric applications have been used globally in everyday life. However, conventional biometrics is created and optimi zed for high-security scenarios. Being used in daily life by o rdinary untrained people is a new challenge. Facing this chal lenge, designing a biometric system with prior constraints of ergonomics, we propose ergonomic biometrics design mode l, which attains the physiological factors, the psychological f actors, and the conventional security characteristics. With th is model, a novel hand-based biometric system, door knob h and recognition system (DKHRS), is proposed. DKHRS has the identical appearance of a conventional door knob, whic h is an optimum solution in both physiological factors and p sychological factors. In this system, a hand image is capture d by door knob imaging scheme, which is a tailored omnivis ion imaging structure and is optimized for this predetermine d door knob appearance. Then features are extracted by loca l Gabor binary pattern histogram sequence method and class ified by projective dictionary pair learning.

Keywords- DKHRS (Door Knob Hand Recognition system),DKI(door knob imaging scheme), DPL(Dictionary pair learning), LGBPHS(local Gabor binary pattern histogram sequence).

1. Introduction

We propose a Door Knob Hand Recognition System (DKH RS), which is shaped like a standard door knob, but incorpor ates a customized imaging device, a robust feature extractio n, and a discriminative classification method. When addressi ng the imaging problem device in this space-limited and sha pe-confined case, we propose a simplified catdioptric imagi ng structure, Door Knob

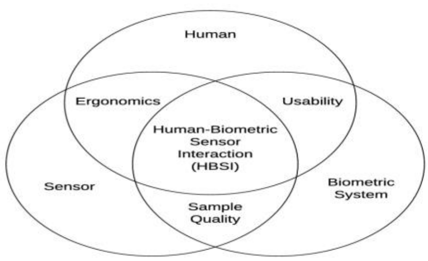
Imaging (DKI) scheme. The DKI captures the surrounding hand skin surface in one omnivision image in a cost-efficien t structure. In the proposed t histograms of dense local featur e from DKHRS images. The features are classified using the dictionaries learned by projective Dictionary Pair Learning (DPL). Combining DKI scheme, LGBPHS method, and DP L method, we make the proposed DKHRS effective and effi cient under the ergonomic constraints.

2. Ergonomic Biometric design

a. Ergonomics Studies in Biometrics

Ergonomics (human factors) is to design products and syst ems in considering the interaction with people. In biometrics , physical ergonomics and cognitive ergonomics are two crit ical factors. Physical ergonomics focuses on physical motio n related traits including human anatomical, anthropometric, physiological, and biomechanical characteristics. Cognitive ergonomics focuses on human–system interaction related

Fig 2.a: HBSI model of interaction between human, biomet ric sensors, and biometric system



mental activities including perception, memory, reasoning.

In biometric systems, the ideal ergonomic Solution would make the user barely notice the authentication process. Also, a biometric system with poor ergonomics would jeopardize the quality of collected bio- metric sample make the user bar ely notice the authentication process.

A biometric system with poor ergonomics would jeopardize the quality of collected bio- metric samples.

HBSI model is shown in Fig2.a, focuses on the interactions between target subjects and the biometric sensors. HBSI mo del utilizes the metrics from both biometrics and ergonomics to assess the functionality and performance of biometric sys tems. Human-sensor intersection focuses on the physical erg onomics. Human-biometric system intersection represents th e interactions between users and systems, which include sen sors, software, and implementations of systems. The aim of t his intersection is comprised of three factors: 1) effectivenes s, 2) efficiency, and 3) satisfaction.

3. DKI scheme

DKI the imaging structure is simplified to capture the surrounding area near the case of the device only.DKI scheme is shown in Fig This simplified scheme is composed of a door knob case, a flat reflective mirror, a lens of a large angle of view, and a camera. The door knob case is transparent. It holds the hand and enables the capturing of the hand image.

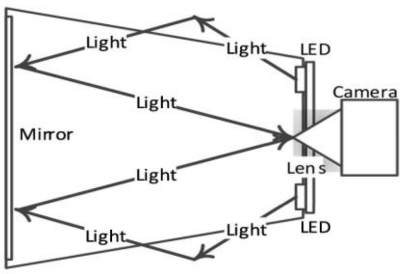


Fig. 3.a: DKI scheme is simple and cost-effective capturing the surrounding hand texture in one image.

The flat mirror reflects the image of the hand. The camera and the lens capture images of the reflected image of the surrounding through the transparent case.

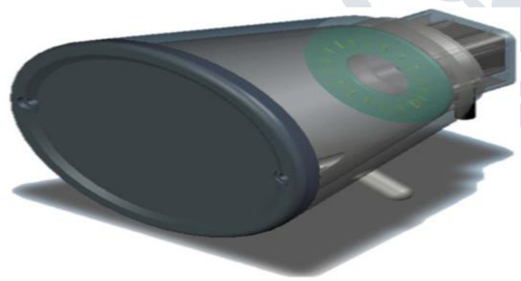


Fig.3.b:image-capturing device of DKHRS was made following the DKI

image of the surrounding through the transparent case. With DKI scheme, the device can capture the image of the hand holding the device. Furthermore, to stabilize the position of the hand, there are two holding pegs fixed on the lower surface of the door knob case. The image-capturing device of DKHRS, which is made following DKI scheme, is shown in Fig.3.c. The device is made of these components listed below. The door knob is made of acrylic glass. The acrylic is a kind of highly transparent plastic (transparent for over 90% energy and across a large spectrum including visible light and near infrared light) and is also strong, lightweight and easy to process. The flat mirror reflects over 95% energy of light across the visible and infrared spectrum with a customized coating. The camera and the lens together capture the surrounding

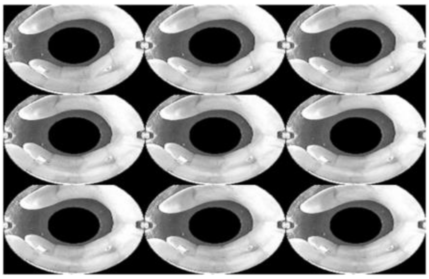


Fig.3.c: Images captured by DKHRS.

image in the mirror. The frame grabber digitizes analog images to digital images for further processing.

The components are as follows.

1) Acrylic transparent door knob.
2) Over 95% full spectrum reflective mirror.
3) White LED board.
4) 6 mm focal length pinhole lens.
5) 1/3-inch miniature camera.
6) A USB 2.0 frame grabber.
7) Raspberry Pi Camera

The camera's image sensor has a native resolution of 5MP. It supports full resolution still images up to 2592x1944 and video resolutions of 1080p30 and 720p60.

4. DKHRS prototype

DKHRS captures hand images surrounding the door knob, as depicted in Fig. A biometric feature should be unique, stable, and persistent. DKHRS captures the hand image surrounding the doorknob, as depicted in Fig. 6. The feature of a DKHRS image is the texture feature on the skin of the hand. Different from a palm print image or a fingerprint image, a DKHRS images an image of a hand in the holding gesture. Though this hand image is not taken with a flattened standard pose, the holding gesture of the hand still can be stable and reliable. Meanwhile, this hand image contains unique texture features. After preprocessing of the raw DKHRS image, the features of a DKHRS image can be extracted with LGBPHS method. After the extraction, the features are classified by DPL.

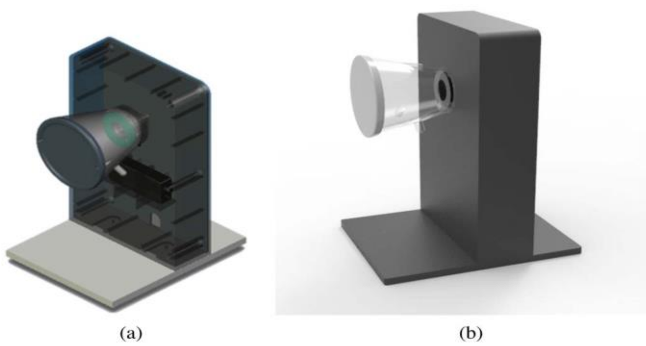


Fig.4. Prototype system used in the data collection. The DKHRS is installed in a door simulator, which is a black acrylic box and is positioned on a balance board

5. Raspberry-pi: For Image processing, Comparing and storing

It is a small single board computer developed to promote teaching of basic computer science.
It runs on 1.4 GHz 64-bit quad core processor with 1Gb of RAM. It also consists of on-board Wi-Fi, Bluetooth.
The Operating system used is Raspbian OS.
Raspberry-pi works on python coding ,here in the DKHRS we are implementing the system using Raspberry-pi which has many advantages such as it is easy for set up because of of its small size and weight and also it has a storage element for the storage purpose and once the code is dumped into the Raspberry-pi there is no need to dump the code again and also of any external system.

6. Methodology

a. Palm Line Extraction and Representation

Palm lines, including principal lines and wrinkles, are a kin d of roof edge. A roof edge is generally defined as a disconti nuity in the first-order derivative of a gray-level profile . In o ther words, the positions of the roof edge points are the zero -cross points of their first-order derivative. The magnitude o f the edge points second derivative can reflect the strength of these edge points. These properties can be used to dete

ct palm lines, but the directions of palm-lines are arbitrary, a nd it is very difficult to obtain their directions directly from noisy images.so in this section we discuss the detection of p alm lines in different directions and we call lines that are det ected in θ direction θ-directional lines and the detectors that detect θ-directional lines as θ-directional line detectors. Sup pose that I(x, y) denotes an image. We devise the horizontal line detector (0◦-directional line detector). To improve the c onnection and smoothness of the lines, the image is smoothe d along the line direction (horizontal direction) using a one-dimensional (1-D) Gaussian function G_{σ_s} with varianceσ_s,

$$I_s = I * G_{\sigma_s}$$

Where "∗" is the convolve operation, which is used to imple ment linear filtering of the image. Finally, all of the directio nal line images are combined to obtain a line image, denoted as L, as

$$L(i,j) = \bigvee_{all\ \theta} L_\theta(i,j)$$

Where "V" is a logical "OR" operation. After conducting the closing and thinning operations, we obtain the resultant pal m line image. Fig.6.a show the process of palm line extracti on.

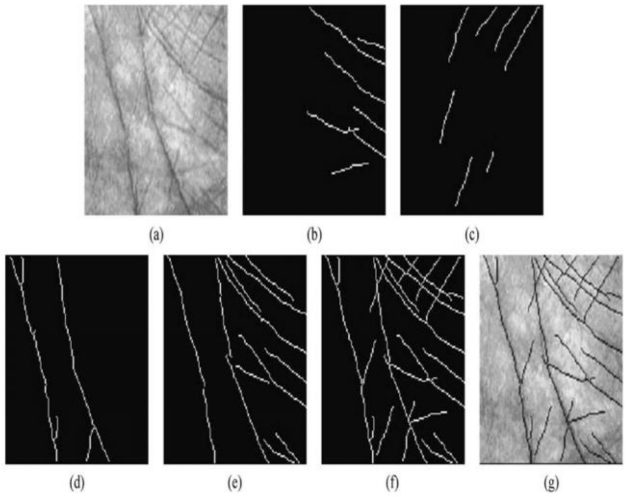


Fig.6. a.: Process of palm line extraction. (a) Original image. (b) 0◦-directional lines. (c) 45◦-directional lines. (d) 90◦-directional lines. (e) 135◦-directional lines. (f) Resultant palm lines. (g) Original palm print overlapped with the extracted palm lines.

Palm print verification, also called one-to-one matching, involves answering the question "whether this person is who he or she claims to be" by examining his or her palm print. In palm print verification, a user indicates his or her identity and thus the input palm print is matched only against his or her stored template. To determine the accuracy of the verification, each sample is matched against the other palm prints in the same database. If the matching score exceeds a given threshold, the input palm print is accepted. If not, it is rejected. The performance of a verification method is often measured by the false accept rate (FAR) and false reject rate (FRR). While it is ideal that these two rates be as low as possible, they cannot be lowered at the same time. So, depending on the application, it is necessary to make a trade-off: for high security systems, such as some military systems, where security is the primary criterion, we should reduce FAR, while for low security systems, such as some civil systems, where ease-of-use is also important, we should reduce FRR.

b. Local Gabor Binary Pattern Histogram Sequence (LGBPHS)

Unlike the mainstream approaches based on statistical learning, we devote to develop a novel no statistics-based face representation approach, Local Gabor Binary Pattern Histogram Sequence (LGBPHS), which is not only robust to the variations of imaging condition but also with much discriminating power. Briefly speaking, LGBPHS is actually a representation approach based on multi-resolution spatial histogram combining local intensity distribution with the spatial information, therefore, it is robust to noise and local image transformations due to variations of lighting, occlusion and pose. Additionally, instead of directly using the intensity to compute the spatial histogram, multi-scale and multi-orientation Gabor filters are used for the decomposition of a face image, followed by the local binary patterns (LBP) operator. For recognition, histogram intersection is used to measure the similarity of different LGBPHS and the nearest neighborhood is exploited for final classification.

c. LGBP Histogram Sequence

Face recognition under varying imaging conditions such as illumination and expression is a very difficult problem. Usually, the variations will appear more on some specific regions in face image. Therefore, we exploit local feature histogram to summarize the region property of the LGBP patterns by the following procedure: Firstly, each *LGBP Map* is spatially divided into multiple non-overlapping regions. Then, histogram is extracted from each region. Finally, all the histograms estimated from the regions of all the *LGBP Maps* are concatenated into a single histogram sequence to represent the given face image. In this system, we employ a Local Gabor Binary Pattern Histogram Sequence (LGBPHS) method, which extracts robust Histogram Sequence.

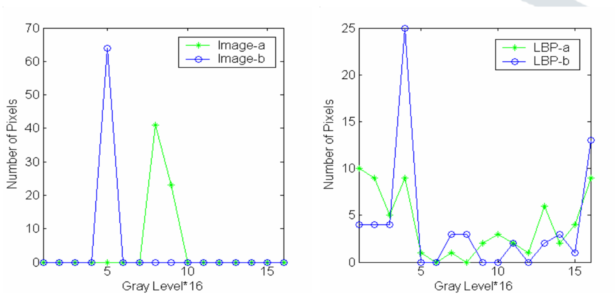
d. Robustness Analysis of the LGBPHS

Evidently, a good face representation should robust to image variations. n order to investigate the robustness of the proposed approach, we compare the histograms of four representations extracted from two images of the same person with different lighting. The four representations are respectively the original image intensity, LBP of the image, Gabor magnitude of the image.

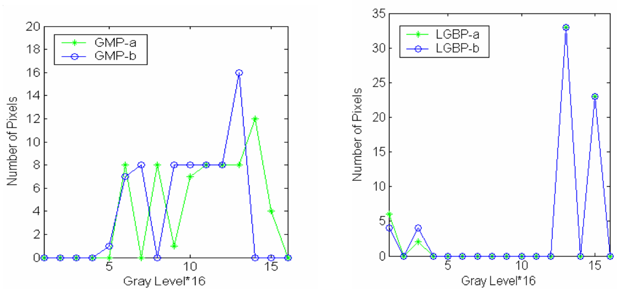
(a) (b)

Figure.6. d. Two face images from the same subject.

image, and the proposed LGBP of the image. We divide the image into regions of the same window size 8□8 pixel array. A white region as shown in Fig. 2 is selected to extract different histograms, and the results are shown in Fig.6.d. One can see clearly that the histograms of the proposed LGBP are the most similar. This implies that face representation of LGBP is robust to the lighting variation.



(a) (b)



(c) (d)

Figure .6. d. Robustness of the different histograms to images with lighting variation.

e. Dictionary Pair Learning

The dictionary learning can extract the internal structure characteristics of the sample data and it plays a very important role in denoising, feature extraction, compressed sensing, pattern recognition and classification. The method considers the inter-class and intra-class incoherence constraints of the synthesis dictionary, and for the analysis dictionary, it should maximize the total scatter and the between-class scatter of the signal after coding, simultaneously. And then the trained incoherence dictionary is used for sparse representation. The method not only preserves the advantage of low computational complexity DPL model, but also it can learn a more discriminative dictionary and make the signal more separable after coding.

Conclusion

In this paper, we propose a novel DKHRS using EBD model, which considers ergonomics in all three design stages. We invent DKI scheme to capture an omnivision hand image. Combining LGBPHS and DPL methods, the proposed system achieves promising recognition performance. In addition, the proposed system shows that designing a biometric system with prior constraints of ergonomics does not definitely means a worse performance.

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