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Unconstrained Palmprint as a Smartphone Biometric

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Abstract—

***Index Terms—* biometrics, security, consumer electronics.**

I. INTRODUCTION

A. Biometrics on Smartphones

TRADITIONALLY found on dedicated devices, biometric systems make use of physiological or behavioral properties of the human body in order to identify or authenticate a person based on a previously learned set of samples [1].

In previous works the use of biometrics on smartphones has been reviewed and considered in detail [2]–[4]. The use of fingerprint technology is well-known and has become highly integrated into certain modern devices [5]–[7]. Face recognition has also been explored for applications on consumer devices [8], [9] but has not been widely adopted in practice, due in part to concerns on the ease with which face data can be captured and used in spoofing attacks [10], [11].

More recently, research into second-generation biometrics has focused on the iris of the human eye. For iris recognition, images are generally captured at near infra-red wavelength. It is challenging to acquire such an iris region in current consumer devices without making significant modifications to the standard camera module or providing a dedicated Near-Infrared (NIR) imaging module [12].

B. Palmprint as a Smartphones Biometric

One important barrier to incorporating additional biometric sensing capabilities into a consumer device is the need to add new hardware. Fingerprints require that suitable sensing technology is available as the initial experience with swipe sensors was highly unsatisfactory [27]. Similarly, iris acquisition will require either modified optical designs, the use of new NIR sensitive CMOS image sensors or a combination of both[13].

New hardware designs are expensive and take time to perfect, thus delaying the market entry of a new biometric technology. But the main camera on today's devices has the capability to capture good quality palmprint data. And improvements in focus and exposure algorithms make this camera quite effective in acquiring a normalized palmprint image across a broad range of lighting conditions. It is worth noting that the main use of palmprint is likely to be as a secondary, confirmatory biometrics rather than a primary, or transactional biometric [14].

Thus, while palmprint has not seen the mainstream use of face, fingerprint and iris biometrics, it is an equally valid candidate for use in smartphones and has the advantage that no additional sensing capabilities are required. And there is a further advantage – one of the weaknesses of facial images [11] and fingerprints [6] lies in the ease with which high quality samples of these biometrics can be obtained by an attacker. Palmprints are not as easy to acquire without the user's consent as people do not easily leave behind palmprint copies or expose them during daily activities. These considerations when coupled with the ease with which a palmprint can be authenticated by simply holding one's hand at arm's length and taking a picture have provided the primary motivation for this work.

This article presents a literature survey on touchless palmprint recognition on mobile devices and its challenges. It is followed by the introduction of a novel unconstrained palmprint database acquired with several handheld devices. The database imitates the real-world challenges which may be experienced by a smartphone palmprint biometric system.

The database is discussed and compared, bringing it in line with the other established palmprint databases that are more constrained. Baseline experiments are provided and an approach was recommended for smartphone use cases. Finally, the results are compared with the best case performance obtained in more constrained palmprint recognition systems.

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TABLE I
PALMPRINT DATABASES DEVELOPED IN RECENT YEARS

Name	Capture Type	Year	Main characteristics	Number of images	Number of hands	Publicly available
PolyU [28]	Contact-based	2003	Constrained environment	7,752	386	Yes
CASIA [38]	Contact-less	2005	Constrained environment – uniform background, only small pose variation and regulated lighting conditions.	5,502	624	Yes
IIT Delhi [29]		2006	Constrained environment – uniform background, only small pose variation and regulated lighting conditions.	3,290	670	Yes
[28]	Contact-less	2017	Constrained environment – uniform background and uniform hand pose, with regulated lighting conditions. Large scale database with high quality images.	12,000	600	Yes
UPM [39]	1 Smartphone Camera	2011	Intended for hand geometry, although contains the palmprint region; background is uncomplicated, which simplifies the segmentation of skin regions.	30 per participant	Not specified	No
[34]	1 Smartphone Camera	2011	Only hands with open fingers; no information regarding the acquisitioning environment.	252	84	No
DevPhone [35]	1 Smartphone Camera	2013	Users did not receive any instructions when capturing palmprints; controlled acquisition using a square guide displayed on the screen; no information about the environment of acquisition.	600	30	No
BERC DB1 BERCD B2 [36][42]	1 Smartphone camera	2015	'Wild' acquisitioning conditions; a controlled hand orientation using a visual guide on the device screen; makes use of flash illumination.	8,957 9,224	120	Not currently
PRADD [41]	2 Smartphone Cameras and 1 Compact Camera	2012	Only hands with open fingers, against a surface covered with black cloth. Images not captured by the device's user. Two lightning cases - office and daylight.	12,000	100	Not specified
[37]	1 Smartphone Camera	2016	Users had to position the palm in a circular guide displayed on the screen of the device. Each user filmed 3 short videos of the palm.	186 short videos	62	Not specified
Proposed Database: NUIG_Palm1	5 Smartphone Cameras	2017	Users did not receive instructions on how to acquire palmprint images; two extremes of lighting conditions - indoor light conditions, normal daylight conditions; 5 different smartphones	1,616	81	Yes

II. RELATED LITERATURE & CONTRIBUTION

A. Contactless Sensing of Palmprints

Palmprint recognition as a biometric feature can be used either in its latent [15], and low resolution form [16]–[18]. The former category is part of the field of forensics and requires high resolution images of at least 500 ppi, whereas the latter only uses 100 ppi and are enough for access control applications.

The low resolution palmprint information can be extracted using texture descriptors. Wu et. al [19] use a derivative of Gaussian filter (DoG), while Sang et. al [20] have extracted Local Binary Pattern (LBP) [21]. Geometric features, including Difference of Gaussian, Hessian and others have been used [22].

The best performing approaches palmprint feature extraction techniques are the ones encoding the orientation at pixel level. While the Competitive Code (CompCode) [23] uses a set of Gabor filters with 6 orientations and encodes the minimum response based on a winner-take-all rule, the Robust Line Orientation Code (RLOC) [24] makes use of a modified Radon transform and uses a similar rule. Orthogonal Line Orthogonal Features (OLOF) [25] uses six elliptical Gaussian filters and compares each orthogonal pair to generate one bit feature code. Results are further improved by combining OLOF with SIFT [26]. A Histogram of Oriented Lines (HOL) [27] is computed using CompCode and RLOC features in cells of size 2x2 and was compared to Histograms of Oriented Gradients (HOG) extracted from the palmprints' gradient. A collaborative representation of CompCode, together with a large contactless palmprint database was proposed by Zhang et al [28].

Recently the number of filter orientations used for CompCode and RLOC has been challenged, and a faster, better performing version was proposed [29]. By employing only one orthogonal pair of filter responses, both matching speed and performance are greatly improved. Another novelty represents the introduction of Difference of Vertex Normal Vectors (Don) [30], which extracts 3D information from a 2D palmprint image.

These results are based on conventional databases which have been acquired in constrained conditions of lighting and hand pose. While the Hong Kong Polytechnic University database (HKPU) [31] provides images of scanned hands, IIT-Dehli database (IIT-D) [32] offers touchless hand images from an enclosed structure. Both databases make for an environment where the segmentation of the hand from the background is not the greatest challenge. And it is understandable the case be so, but at the moment we are looking to extend the capabilities of existing matching systems and include palmprint images acquired with non-professional devices in uncontrolled conditions, where alignment errors are one of the biggest factor affecting match rates. To overcome such challenges, Ito et al

[33] propose a novel palm region extraction method which is robust against hand pose variation, but relies on the segmentation from the background, thus making it sensitive to segmentation artefacts. Similarly, the approach of ElSayeed et al [34] relies on uncluttered background and open fingers. Aykut and Ekinci [35] employ an Active Appearance Model (AAM) to extract the Region of Interest (ROI) but only allow one hand posture. If the ROI is successfully extracted, then potential misalignments can be managed by the matching of SIFT features, as carried out by Zhao et al [36]. Even though these alignment approaches are intended to be used in touchless palmprint systems, they have not been used on smartphones.

B. *Research on Palmprint on Mobile Devices*

Only in recent years have researchers begun to consider the smartphone as a means of acquiring palmprint images with the embedded rear camera [37]–[40]. Choraś and Kozik [37] used a combination of classifiers and Eigen-palms to extract and match palmprint features. When using 50 randomly created classifiers they obtain an EER of around 3.3%, as opposed to the 50 manually created classifiers that give an EER of 7%. Aoyama *et al* [38] used a square guide, together with skin color segmentation and Band Limited Phase Only Correlation (BLPOC) for feature extraction. The authors compare the efficiency of their algorithm with a database of their own, together with HKPU (e.g. contact-based) and CASIA (contact-less)[41]. This yields EER of around 4% for their database, whereas PolyU generates an EER of 0.05% and CASIA an EER of 0.5%. Kim *et al* [39] extract the ROI's features using a local orientation histogram of palm lines based on CompCode. In order to normalize the hand's posture variation a hand shaped guide was used on the smartphone's screen. Furthermore, to make the algorithm more robust to lighting variation, the embedded flashlight was turned on during the image acquisition. Based on a database that the authors have collected, an EER of 2.88% was noted, whereas CompCode and OLOF provide EER of 6% and 5% respectively. Using the same database, Li and Kim [42] introduce a Local Micro-structure Tetra Pattern. Tiwari et al [40] implement a system on a smartphone which matches SIFT and Oriented FAST and Rotated BRIEF (ORB) features. They tested the influence of histogram equalization pre-processing before the ROI extraction, and reached the best result of 5.5% EER with an accuracy of 96.07% in the case of SIFT features with the pre-processing stage. The least performant results of 27.2% EER and 73% accuracy were given by ORB features with no pre-processing.

A palmprint recognition system intended to operate in a smartphone specific environment firstly needs to be robust to many variations associated with handheld devices – of which a few are lighting conditions, hand rotation and hand pose. A database that can support all these challenges has not yet been made available. However, de Santos Sierra *et al* [43], [44] describe a hand biometrics database that was part of their research around hand geometry, which is a biometric feature distinct from the palmprint. According to the authors, the only restriction imposed on the participants was to maintain a distance of around 15-20 cm between the camera and the hand.

Secondly, it needs to be consistent throughout several devices. An initial contribution in this area was made by Wei et al [45] with the introduction of a database of palmprint images acquired from 3 different devices - 2 smartphones and a compact digital camera. A number of common feature extraction techniques were matched in various training and testing scenarios, demonstrating the inter-device operability of a smartphone palmprint system. However, these results were obtained in significantly constrained conditions in terms of image acquisition. The hands were required to have fully extended open fingers against a uniform black cloth placed on the ground. Furthermore, in some cases the devices were handled by other people, which does not fit the use case of self-authentication [45].

Unfortunately, the databases mentioned earlier [37]–[40], [45] have not been made publicly. The lack of a publicly available palmprint database able to mimic the variations of smartphone use cases has encouraged the development of the database entitled 'NUIG_Palm1', capable of covering the majority of variations found in an unconstrained environment.

C. *Contributions of this Work*

The primary contribution of this work is to demonstrate the feasibility of employing unconstrained palmprint biometrics across a range of contemporary smartphones. There is no specialized hardware and thus palmprint authentication can be readily implemented. Further, it is shown that biometric authentication is essentially portable between devices in an unconstrained environment.

In support of our primary contribution a new database of palmprint images obtained for multiple handheld devices and based on an unconstrained acquisition protocol is presented. This database is, to the best of our knowledge, unique. It offers a set of unconstrained palmprint images acquired from 81 individual subjects, each with a dataset acquired with five different smartphones. The goal is to represent practical acquisition conditions where users are only asked to capture the entire area of their palm in a substantially open/flat presentation. No further instructions were given to the subjects participating in this research. The database is provided with an annotated ground truths to provide a baseline for comparison between recognition algorithms.

Several preliminary experiments are also detailed to demonstrate the feasibility of this unconstrained acquisition mode. This initial study demonstrates acceptable performance as a secondary biometric. The use of palmprint in a two (or three) factor authentication scheme requires that its use is convenient for the user and it does not require additional sensing capacity to be added to a CE device. Unconstrained palmprint is ideal for such a use case and is faster than waiting for an SMS message and typing this back into your device. It can also serve as a presence/liveness check for a primary authentication means such as an iris or fingerprint scan – there have been several recent examples of spoofing both of these biometric techniques on smartphones [46].

III. Multi-Device Palmprint Database

A. *Initial Proof-of-Concept Dataset*

When implementing a palmprint recognition system on a mobile device, one needs to take into account the nature of the images that are used. The user should restrict as few acquisition

(a) (b) c)

Fig. 1. Image samples from (a) PolyU database (above) and IIT Delhi (below); (b) The proposed database; c) ROI extraction using new coordinate system determined by points X12 and X34

conditions as possible, mainly because of the profile of the handheld imaging capabilities, but also because the user experience should be straightforward and somewhat enjoyable. The camera's environmental conditions vary strongly, from very sunny areas to dark rooms, the rotation of the hand also varies, but most importantly, the background's content is completely 'wild' – all these factors create complex scenarios for pre-processing algorithms to deal with.

An initial Proof-of-Concept (PoC) dataset has been collected from users using 4 different mid-market smartphones from late 2012 and 2015.

The variations associated with this database are detailed in Table II. Based on these parameters and related variables, the acquiring session consisted of taking 27 images per smartphone for every user. Reducing the hand orientations to the user's choice meant that the images were closer to how palmprints would be acquired in real life and provided a smoother interaction with the device – a quality that is critical to all consumer devices. The lighting conditions were reduced to two setups, whereas two backgrounds were used.

B. *Design and Acquisition of Data for the Full Database*

Each participant was asked to choose one hand and take pictures of it against 2 distinct backgrounds representing 2 specific cases: i) a cluttered background composed of several images with a number of calibration patterns and ii) skin like background, containing wooden texture. Two Lighting conditions were considered – 'inside dark' and 'indoor normal'. This resulted in 4 images per device, with a total of 20 images per person. A few samples are provided in Fig.1.b) alongside palmprint images from HKPU and IIT-D databases in Fig.1.a). Users were not restricted to one particular hand orientation, they were free to choose whatever was most comfortable for them – including the distance from the hand to the camera. The camera settings were set to "Auto" the entire time with the flash turned off.

C. *Main Database Characteristics*

The proposed database provides researchers with a rich set of images taken from 81 individual subjects of mixed gender, and ages ranging from 19 to 55 years old. A total of 5 smartphone devices were used to acquire images for each subject, as detailed in Table III; images of each user's palmprint were acquired at two distinct lighting levels and in two distinct background conditions. There are thus 20 images of palmprints per subject or 1,616 images available in the main database. Note that only one hand was used per subject as the workflow reflected a user's natural predilection to use their lead-hand to hold the device, thus capturing an image of their secondary hand. In order to increase the relevance of the database, for this paper all right hand images were flipped vertically so that all samples can be considered as coming from a left hand.

This is the first publicly available wild multi-device database to be used for testing palmprint biometrics.

TABLE II
VARIATIONS OF THE PROOF OF CONCEPT DATABASE

Parameters	PoC Database	Final Database
Light	Indoor Dark (6 EV or 160 lux) Indoor Normal (7.5 EV or 450 lux) Inside Bright (13.5 EV or 28,900 lux)	Indoor Dark (6 EV or 160 lux) Indoor Normal (7.5 EV or 450 lux)
Background	Poster – complex scenes Real objects scene Wooden Surface	Poster – complex scenes Poster – wooden surface
Hand rotation	Horizontal Vertical Oblique	User's choice

TABLE III
DEVICES USED FOR DATABASE ACQUISITION

Device #	CPU	GPU	Sensor Resolution	Lens f-number	Month of Launch
Device1	6 cores	2 cores	16 MP	f/1.8	April 2015
Device2	4 cores	4 cores	16 MP	f/1.9	April 2015
Device3	2 cores	3 cores	8 MP	f/2.4	Sept. 2012
Device4	2 cores	6 cores	12 MP	f/2.2	Sept. 2015
Device5	8 cores	8 cores	13 MP	f/2.0	April 2015

IV. BASELINE EXPERIMENTS

A. Region of Interest (ROI) extraction and pre-processing

A generic processing pipeline requires the palmprint to be extracted from the hand in a consistent manner. In this paper the finger bases were marked with 5 points, where the 3rd one marks the central finger valley. If we denote the first two points X1, X2 and the last two points as X3 and X4, then the middle point of the segments are represented by X12 and X34. They are then used to create a new coordinate system to rotate and align the palmprints, as demonstrated in Fig. 1c), where the extracted ROI is contained within the green square. These landmarks and the extracted ROIs are provided as benchmarks in future tests related to hand detection.

B. Experimental Setup

Experiments are performed in the proposed palmprint database to provide a set of baseline results. Several feature extraction methods are employed in the baseline experiments to obtain a diversified set of discriminative features.

- Competitive Code (CompCode) [23] is one of the most used algorithms for feature extraction within the context of palmprints, thanks to its efficiency of encoding information with only 3 bits, making it ideal for low-memory conditions. It uses a family of 2-D Gabor filters with 6 orientations and computes the filter responses of the ROI template, to then apply a competitive rule (2)

$$C_i = I(x,y) * \psi_{R,i}(x,y,\omega,\theta_i), \mathrm{i} = 1,\ldots,6 \tag{1}$$

$$C = arg\ min_i(C_i) \tag{2}$$

where I is the input ROI template, *(x,y)* are the pixels, $\psi_{R,i}$ is the real part of 2D-Gabor filter response with radial frequency ω and orientation θ_i.

- Robust Line Orientation Code (RLOC) [24] is defined as a modified finite Radon transform, which is a summation of image pixels over a certain set of lines (3):

$$r[L_k] = \sum_{(i,j)\in L_k} f(i,j),\ k = 1,\ldots,6, \tag{3}$$

,where $[L_k]$ is the set of points that make up a line on a 9x9 lattice which moves across the ROI template. $f(i,j)$ is the real function defining this line. To extract RLOC, the same 6 orientations are used as in CompCode. A competitive rule is then applied to obtain the final code (4)

$$R = arg\ min_k(r[L_k]) \tag{4}$$

- A Fast implementations of CompCode and RLOC was defined in [29] and reported better overall results than their original implementations. By reducing the number of filter responses being used, from 6 to 2, a more discriminative feature is obtained. The selected 2 orientations need to be orthogonal, therefore there are 3 pairs of orientation for CompCode and RLOC defined as (5) and (6):

$$C_F = arg\ min_i(C_i, C_{i+3}), i = 1,..,3 \tag{5}$$

$$R_F = arg\ min_j(r[L_k], r[L_{k+3}]), k = 1,..,3 \tag{6}$$

According to the authors, the pair of orthogonal orientations chosen for the fast implementation does not matter, but some differences were noted in the experimental part of this paper. As a notation, every fast implementation of CompCode and RLOC contains the pair number used for that feature extraction, as mentioned in (5) and (6).

- Local Binary Pattern (LBP) [21], [47] is a simple yet powerful texture operator labeling the pixels of an image by thresholding the neighborhood of each pixel, considering the result as a binary number. The value of the LBP code of a pixel (x_c, y_c) is computed with (7):

$$LBP_P = \sum_{p=0}^{P-1} s(g_p - g_c)2^p,\quad s(x) = \begin{cases} 1, if\ x \geq 0; \\ 0, otherwise \end{cases}, \tag{7}$$

where P is the size of the kernel, equal to 9, p is the index of the neighboring pixels in the region.

- Orthogonal Line Orthogonal Features (OLOF) [25] is based on 2D Gaussian filters to obtain a weighted average of line-like regions (8).

$$f(x,y,\theta) = \exp\left[\left(\frac{x\cos\theta + y\sin\theta}{\delta_x}\right)^2 - \left(\frac{-x\sin\theta + y\cos\theta}{\delta_y}\right)^2\right], \tag{8}$$

where θ denotes the orientation of the filter, δ_x and δ_y denote the horizontal and vertical scale parameters. Throughout experiments the values $\delta_x = 1.8$ and $\delta_y = 0.5$ were used.
An orthogonal filter is obtained with (9):

$$OF(\theta) = f(x,y,\theta) - f\left(x,y,\theta + \frac{\pi}{2}\right) \tag{9}$$

Three ordinal filters,$OF(0)$,$OF(\frac{\pi}{6})$ and $OF(\frac{\pi}{3})$ are applied to obtain three bit codes based on the sign of filtering results.

- Difference of Vertex Normal Vectors (DoN) [30] represents a 3D feature descriptor recovered from a 2D image. Each point/pixel p_i on the image plane is corresponding to a vertex v_i on the palmprint surface. For every point p_i, having two neighboring regions $R_i^1$and R_i^2, its DoN feature is computed with (10):

$$DoN(i) = \tau\left(\sum_{j\epsilon R_i^1} z_j - \sum_{j\epsilon R_i^2} z_j\right), \tau(\alpha) = \begin{cases} 0, \alpha < 0; \\ 1, \alpha \geq 0. \end{cases} \tag{10}$$

Practically, in order to construct the feature extractor a filter needs to be constructed using (11)

$$f_{i,j} = \begin{cases} 1,\ if|i| > |j| \\ -1,\ if|i| < |j| \\ 0,\ otherwise. \end{cases} \tag{11}$$

where i,j are the indexes $i,j \in [-B,B]$. The filter size is $(2B+1)\times(2B+1)$. In order to obtain the final feature image, the palmprint is convolved with the filter (12):

$$F = I(x,y) * f_{i,j} \tag{12}$$

The dimensionality of feature vectors was varied from 32x32 pixels to 128x128 pixels. Computationally light feature extraction techniques are chosen in order not to exhaust the computation resources of a smartphones.

C. CRC_RLS Classification Strategy

As palmprint recognition is a small sample size classification problem, a collaborative representation classifier with regularized least squares (CRC-RLS) is used to determine the identity of the query image [48], [49].

Let $D = [D_1, D_2, \ldots, D_k]$ be the dictionary which denotes the training palmprint images of the k subjects (available in the database). $D_i = [v_{i,n_1}, v_{i,n_2}, \ldots v_{i,n_i}]$ are the training palm images of the i^{th} person and the total number of training palm images of the same person is denoted as n_i. A query palmprint image y can be collaboratively coded over the dictionary D by using (13) [48]

$$a = Xy \tag{13}$$

where

$$X = (D^T D + \gamma . I)^{-1} D^T \tag{14}$$

where γ is the regularization parameter and I is the identity matrix. The regularized residual ε_i for each subjects i in the dictionary D over this coding scheme is calculated using (15)

$$\varepsilon_i = \|y - D_i . a_i\|_2 / \|a_i\|_2 \tag{15}$$

From the regularized residuals, the identity of the query image y can be calculated with (16)

$$Identity\,(y) = arg\,min\,(\varepsilon_i) \tag{16}$$

This specific choice of classification scheme is employed based on not only its success rate in face recognition, gender classification etc., but also because it is up to 1600 times faster than the state of the art sparse representation based classifiers [3]. Such a high performing, computationally light classifier may be widely adopted in resource constrained consumer devices such as smartphones.

The baseline experiments are classified into three main categories - (1) Cross-device Palmprint Matching, (3) Classification Strategy Evaluation and (2) Device-specific Palmprint Matching.

1) Cross-device Training Set (CD_Train)

All the images that are part of a lighting/background setup are used as the training set one at a time. For instance, images captured in cluttered background under 'indoor normal' lighting condition with all five devices make up the training set of images (total of 405 images), while the rest make up the testing set (total of 1215 images). Matching experiments are conducted by varying the template size, from 32x32 to 64x64 and 128x128 pixels.

The training set is then changed to the other setups and results are averaged, giving a better perspective of the performances and challenges of the database.

2) Classification Strategy Evaluation

This set of experiments is designed to compare the recommended strategy with several feature extraction techniques and with more traditional classification strategies such as Support Vector Machines (linear kernel), Nearest Neighborhood (number of neighbors optimized for the training set) classifiers and Fisher Discriminant Analysis [50]. The template feature sizes are the ones with best performances in the CD_Train case. Setup 1 was used, with 'indoor normal' lighting conditions.

3) Cross-device Testing Set (CD_Test)

The training set for each class is using all the images from one device at a time. This results in training with 4 palmprint images for each class, thus covering both lighting conditions (total of 324 images). The remaining 16 images from the other devices are used for testing (total of 1296 images). The template sizes used are the ones which yielded the best results in the cross-device experiment.

This experiment represents a more mature recognition strategy where the database can contain various imaging conditions. Such a scenario is viable when the recognition system updates the enrolled images over a period of time as the system encounters images acquired in conditions that are considerably different from the previously enrolled images' environment.

V. RESULTS

A. Cross-device Training Set

The CD_Train matching results are presented in Table IV, indicating that the CRC_RLS classifier is fairly robust to alignment errors, considering the matching is done at pixel level. Please note the fast implementations of CompCode and RLOC contain 'Fast' in their name and an indication of the pair used for their computation, as detailed in (5) and (6).

The results reflect the appropriate size of the template for each feature extraction technique. While in most cases results are better when the template size is 64x64 pixels, LBP, OLOF, Fast-Comp2 and Fast-Comp3 achieve their best recognition rate (RR) around 73% and equal error rate (EER) around 13% at 32x32 pixels. The best result is achieved by the Don feature at around 80% RR and 10% EER, closely followed by Fast-RLOC2 and Fast-RLOC3, at around 77% RR and 11% EER. The other features go only slightly above 70% RR and have high EER.

B. Classification Strategy Evaluation

C. Cross-Device Testing Set

Further, Receiver Operating Characteristic (ROC) curves for the CD_Test recognition experiments are provided in Fig. 2, where it can be observed that results are better than CD_Train case. This suggests that training with more images from the

TABLE IV
AVERAGED RESULTS: CROSS-DEVICE RECOGNITION RATES (RR) AND EQUAL ERROR RATES (EER) OF PALMPRINT IMAGES R

Template Size	32x32		64x64		128x128	
Feature Extraction	RR (%)	EER (%)	RR (%)	EER (%)	RR (%)	EER (%)
CompCode	67.03	14.03	69.81	15.69	56.68	21.98
Fast-CompC1	66.64	14.60	69.15	16.63	54.59	25.23
Fast-CompC2	73.12	12.31	71.31	15.68	55.72	25.62
Fast-CompC3	70.74	13.11	69.07	16.94	51.37	27.90
RLOC	70.57	12.20	*77.06*	*10.88*	71.46	15.37
Fast-RLOC1	67.32	13.50	73.54	13.10	67.73	18.29
Fast-RLOC2	70.06	12.58	*76.81*	*11.67*	69.79	17.04
Fast-RLOC3	69.44	12.31	75.61	10.99	60.47	15.82
LBP	72.71	13.61	72.59	14.89	68.37	15.96
OLOF	73.02	12.94	70.47	16.34	56.58	24.37
DoN	77.67	9.49	*79.87*	*10.06*	71.77	15.36

TABLE V
RECOGNITION RATES FOR CD_TRAIN TRAINING USING VARIOUS CLASSIFIERS

Classifier	**Linear SVM**	**K-Nearest Neighbour**	**Fisher Discriminant Analysis**	**CRC_RLS**
Feature Extraction	RR (%)	RR (%)	RR (%)	RR (%)
CompCode	69.88	67.98	69.22	70.20
Fast-Comp1	70.12	79.34	70.21	71.52
Fast-Comp2	74.68	75.72	65.35	73.90
Fast-Comp3	75.59	77.20	66.34	72.92
RLOC	78.19	79.59	78.19	78.84
Fast-RLOC1	73.09	78.85	74.16	74.73
Fast-RLOC2	78.27	81.23	78.68	78.60
Fast-RLOC3	74.07	56.13	76.13	76.46
LBP	73.99	79.67	67.98	73.66
OLOF	74.07	77.53	69.47	71.93
DoN	74.49	63.79	76.05	81.07

TABLE VI
GENUINE ACCEPTANCE RATES (GAR) CORRESPONDING TO 0. 01% FALSE ACCEPTANCE RATE IN THE CD_TEST CASE

Feature Extraction	TAR value
DoN	90.05%
Fast-RLOC2	86.50%
RLOC	86.00%
Fast-RLOC3	85.34%
Fast-CompC3	84.65%
Fast-CompC2	83.72%
OLOF	82.48%
Fast-RLOC1	82.40%
LBP	81.87%
CompCode	76.70%
Fast-CompC1	75.31%

same device is more important than having images from several devices. Of all cases, when training the CRC_RLS classifier with images from Device2 (Fig.2 b)) the best RR and EER is reached by DoN with 87.81% and 6.10%. Whereas Device2 provides the best RR and EER, the lowest are resulting from Device4 (Fig.2 d)). Instead of correlating this result with the sensor's resolution, it is more appropriate to justify it with the device's firmware, more exactly image stabilization and overall behavior to low light scenes. As it can be noted from Fig.2 c), Device3, which represents another model of the same family of devices, follows a similar trend. Device5 is close to Device3 in terms of performance.

If we are to consider the value of 0.01% for False Acceptance Rate (FAR) as benchmark for a reliable biometric system, then DoN gives the best result in CD_Test, with a Genuine Acceptance Rate (GAR) of 90.05%

Table VI outlines the Genuine Acceptance Rate (GAR) of the best performing case of CD_Test, having as reference the False Acceptance Rate (FAR) of 0.01%, as displayed in Table VI.

This result should not be considered as being a direct consequence of the device's shortcomings, but a testament to the difficulty of using images acquired in a wild environment. Aspects such as image sharpness and alignment of palmprints need to be taken into consideration and mitigated.

D. Best Performance Comparison with Existing Palmprint Databases

This section compares the best performance found in the literature on various palmprint databases with the best performance obtained in the proposed unconstrained database. Note that the publicly available palmprint databases are acquired in constrained environments with dedicated acquisition devices in uniform backgrounds. Such a comparison is given in Table VII.

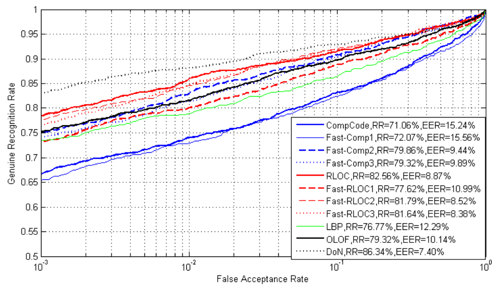
VI. CONCLUSIONS AND FUTURE WORK

This paper demonstrated the feasibility of user authentication on smartphones based on palmprint biometrics. Literature on touchless palmprint recognition on mobile devices and its challenges were outlined. A novel, unconstrained palmprint database is collected using multiple smartphones under varying image acquisition conditions. The publicly available palmprint databases are acquired in constrained environments with dedicated acquisition devices in uniform backgrounds. Unlike such databases, the proposed database is expected to mimic the real-world use case of palmprint biometrics as a user authentication on smartphones

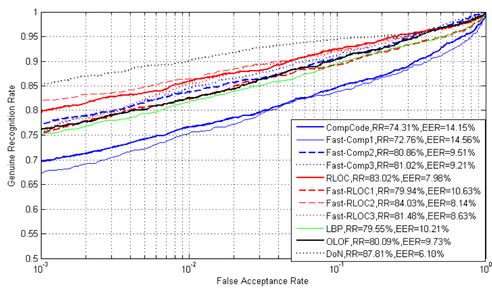
Future work includes increasing the size of the database to 100 users, along with multiple sets of samples for the same user. Furthermore, additional approaches for ROI alignment will be considered that can be employed during the acquisitioning stage for a smoother human computer interaction. The applicability and robustness of these techniques will also be investigated when applied to the multi-device dataset.

TABLE VII
BEST RESULTS FOR SMARTPHONE PALMPRINT DATABASES

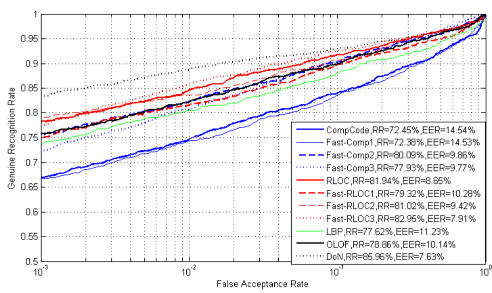
Database	Algorithm used	Lowest EER
BERC DB1 [42]	Local Micro-structure Tetra Pattern	1.11
BERC DB2 [42]	Local Micro-structure Tetra Pattern	1.69
DevPhone [38]	BLPOC	4.00%
Proposed Database 'NUIG_Palm1'	CRC_RLS with DoN	6.10%



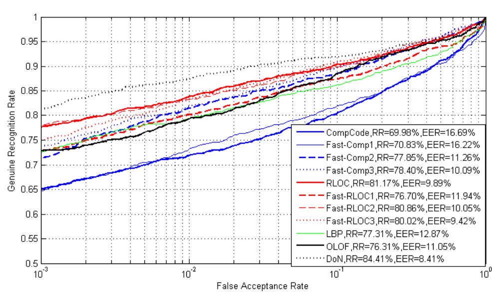
a)



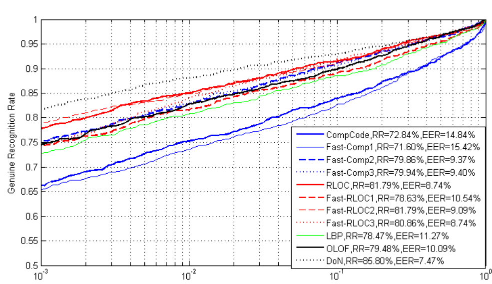
b)



c)



d)



e)

Fig. 2. ROC curves, Recognition Rates (RR) with Equal Error Rates (EER) results for device-specific training sets with CRC_RLS classifier for palmprint matching. Each setup used as training set the images originating from one device and tested the match rate with remaining images, from the other 4 devices. Training set contains the images of a) Device1, b) Device2, c) Device3, d) Device4,e) Device5.

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