Palm Vein Database and Experimental Framework for Reproducible Research

Pedro Tome and Sébastien Marcel
Idiap Research Institute
Centre du Parc, Rue Marconi 19, CH-1920 Martigny, Switzerland
{pedro.tome, sebastien.marcel}@idiap.ch

Abstract:
A palm vein database acquired by a contactless sensor together with an experimental framework freely available for fair reproducible research purposes are described. The palm vein recognition system uses automatic palm region segmentation and circular Gabor filter approach to enhance the veins in the preprocessing, LBP features and histogram intersection as matching. Results are presented comparing two automatic segmentation using the ROI-1 region proportioned by the acquisition sensor and the ROI-2 region generated by the recognition software developed. Complete benchmark results using popular methods and the source code are attached to the database as a reference for other researchers.

1 Introduction

Automatic palm vein recognition has emerged as a reliable technology to provide greater level of security to personal authentication system [WESS05]. Among the various human hand biometric characteristics that can be used to recognize a person, such as geometry, fingerprint, palm print or knuckle print, the palm veins are perhaps the most successful form with highest recognition rates achieved between the different characteristics [MCT12] as palm vein patterns are considered stable and reliable. This means that once a person has reached adulthood, the hand structure, veins and configuration remain relatively stable throughout the person's life [YDS06]. In addition, they can be acquired without contact and require the presence of blood in the veins to be registered, which makes more robust these systems against the liveness problem and the spoofing attacks. The palm vein imaging acquisition requires infrared (IR) illumination (generally, NearIR) and standard cameras with a simple CCD or CMOS sensor. Therefore, palm vein images are grayscale images in which dark grey to black veins appear on the grey background.

Because the scarce number of palm vein databases and the different unclear and complex protocols provided by the databases in the literature, no fair reproducible and comparable research can be carried out. For these reasons, the VERA Palm vein database and the experimental framework are introduced and described in this paper freely available for research purposes at `www.idiap.ch/dataset` and `www.idiap.ch/scientific-research/resources`. Baseline experimental results obtained by the authors using popularly used approaches are also presented.

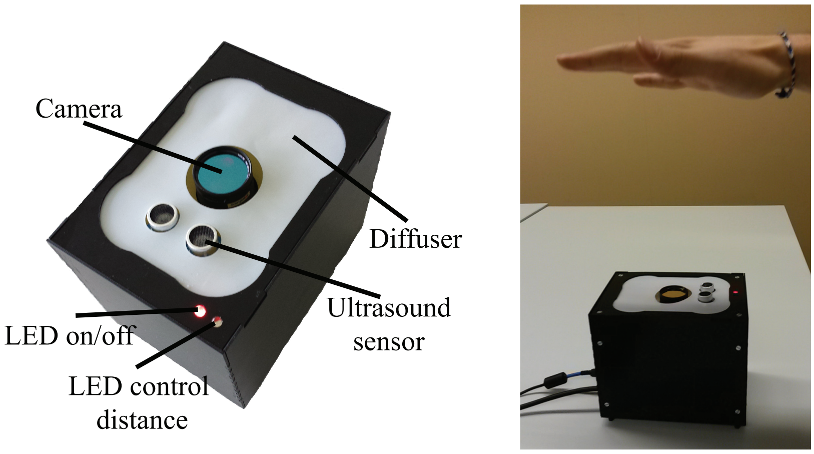

Figure 1: Palm vein prototype sensor description and palm vein image acquisition example.

2 State-of-the-art

The most complete research in palm vein pattern recognition was conducted by Fujitsu in Japan, supported by a patent and described in [Wat08]. The database is comprised of $150,000$ palm vein images from $75,000$ subjects on a different rank of ages. This database was collected for commercial purposes, therefore no details are available and reproduction of the study is impossible. On the other hand, from a non-commercial point of view, there are a scarce number of free available palm vein databases in the literature [HSTR08, KK11]. The most relevant one is the CASIA Multi-spectral [HSTR08], a contactless acquisition from 100 subjects using six different wavelengths (visible, 460, 630, 700, 850 and 940 nm) of the illumination. On the other hand, the PUT database [KK11] is a small database comprises of 50 subjects acquired on a contact sensor using just one wavelength of 880 nm for illumination. It is also important to highlight other database collections mentioned in the literature that are not publicly available such as [MCT12, Lee12]. In this context, researchers working on palm vein recognition built their own acquisition devices to acquire vein pattern images. This resulted in many different proposals for the choice of region of interest (ROI), different positioning equipment, various image parameters such as resolution, and different image collection processes. For those reasons, all these works present different protocols and performance results, which in such different conditions are thus difficult to compare. To the best of our knowledge, there are no works in the literature providing any kind of experimental framework which allows the fair comparison of the performance results similar to the new one that we present here.

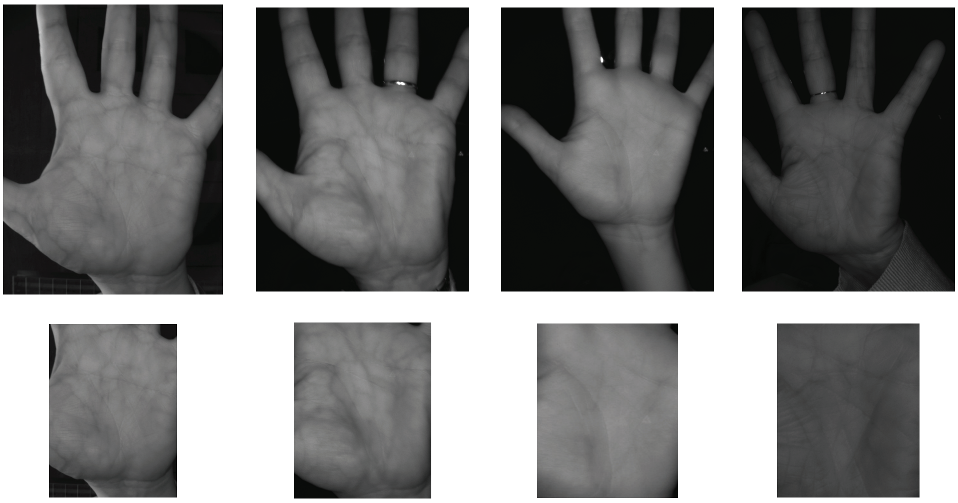

Figure 2: Image examples from the VERA Palm Vein database. First row shows the RAW images acquired and second row shows the ROI-1 images generated by the sensor during the acquisition process. First two columns are male examples while the last two are female examples.

3 Database collection and organization

The database introduced in this paper (called VERA Palm vein) consists of $2,200$ images depicting human palm vein patterns. Fig. 2 shows some image examples from the dataset. Palm vein images were acquired by the contactless palm vein prototype sensor developed by University of Applied Sciences Western Switzerland (HES-SO) and the Idiap research institute comprised of a ImagingSource camera, a Sony ICX618 sensor and an infrared illumination of LEDs using a wavelength of 940 nm. The distance between the user hand and the camera lens is measured by a HC-SR04 ultrasound sensor and a led signal that indicates the user the correct position of the hand for the acquisition. This method of contactless acquisition seems to be natural and feasible. Fig. 1 (right) shows an example of the acquisition process and how the user positioning the hand.

Palm vein images were acquired from 110 volunteers for both left and right hands. For each subject, images were obtained in two sessions of five pictures each per hand. Both sessions were separated by an interval of at least 5 minutes. Images of the left and the right hand of the same person in each session were taken alternately, first the left hand and after the right hand. The palm vein images captured by the sensor are saved as bitmap image using a png format with a resolution of 480×680. The database is divided in two datasets: RAW and ROI-1 data. The *raw* folder corresponds to the full palm vein image and *roi* folder contains the region of interest (palm vein region) obtained automatically by the sensor during the acquisition process (see Fig. 2). Every dataset contains folders for every person whose id includes the gender of the user (M: Male or F: Female). User folders are divided into two sessions: 01 and 02, which contain ten images, five from the left hand and five the right hand. Image file names specify all those items of an information

Protocol	World set		Development set			Evaluation set		
	Clients	# Files	Clients	Enrolment	Probe	Client	Enrolment	Probe
nom L&R	20	400	30	120	480	60	240	960
nom L	20	200	30	60	240	60	120	480
nom R	20	200	30	60	240	60	120	480

Table 1: Database detailed description based on number of images for for the three protocols defined and the different sets.

exactly using the next format: "$UUU\_H\_X\_Y$.png", where UUU defines the user id, H the hand (L: left or R: right), X the session, and finally, Y the number of the acquisition. For example, the image named "$021\_L\_1\_2$.png" is the second image in the first session of the left palm of the 21^{th} user and has the path: ".../021-M/01/$021\_L\_1\_2$.png".

4 Experimental framework

This work presents an open source and extensible experimental palm vein framework called PalmveinRecLib: bob.palmvein[1], which allows fair and reproducible benchmarks on palm vein recognition. This framework includes a complete module for scores analysis and allows to run a complete palm vein recognition experiment, from the preprocessing of RAW images (including segmentation) to the computation of biometric scores and their evaluation. This framework is totally open source and modular, which means that all algorithm parameters are fixed, available and each block can be replaced or improved by new algorithms and approaches. The system implements several baseline methods from the state-of-the-art and is divided on three stages: i) segmentation and normalization, ii) feature extraction, and iii) matching.

In the segmentation process the hand contour is localised by a binarization from grayscale palm vein images. Then the hand landmarks (peaks and valleys) are extracted using the radial distance function (RDF) between the reference point (generally the starting of the wrist) and the contour points extracted [KW14]. The palm region is extracted as a square region based on the located hand landmarks and a scaling and rotation normalization on the extracted palm vein region is performed. Finally, the palm veins are enhanced by using the Circular Gabor Filter (CGF) approach [ZY09]. Once the palm vein region is extracted and normalised, local binary patterns (LBP) are computed to serve as features [MD14] and the histogram intersection metric [SB91] is adopted as a similarity measure to compute the scores.

5 Experimental protocol and baseline results

The VERA Palm vein database is presented with three different protocols: i) nom L&R - normal operation mode, where left and right hand of the same subject are considered

[1] Freely available at `https://pypi.python.org/pypi/bob.palmvein`

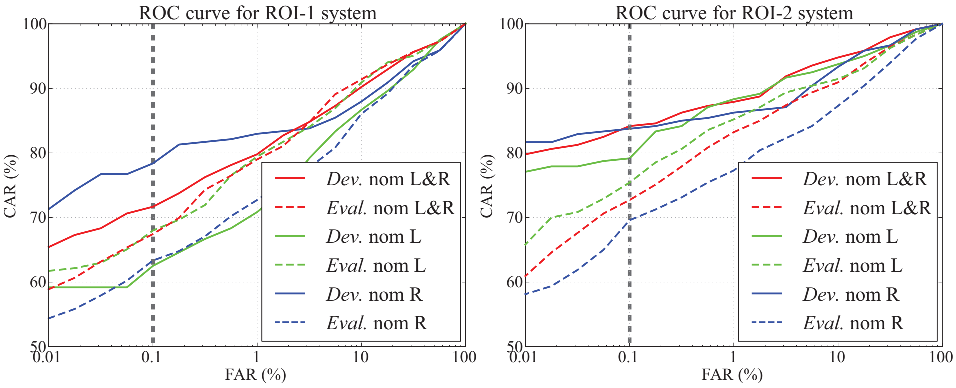

Figure 3: ROC curve of the development set (*Dev.*) and HTER on evaluation set (*Eval.*) for the three protocols defined on the ROI-2 dataset provided by the database and the two ROIs analysed (ROI-1 generated by the sensor during the acquisition and ROI-2 extracted automatically from RAW images by the automatic system).

Protocol	ROI-1 data		ROI-2 data	
	Dev. set EER(%)	Eval. set HTER(%)	Dev. set EER(%)	Eval. set HTER(%)
nom L&R	6.66	7.12	3.75	6.80
nom L	8.42	7.73	4.58	5.90
nom R	7.08	8.93	4.57	9.37

Table 2: Benchmark results of EER on the development set (*Dev. set*) and HTER on evaluation set (*Eval. set*) for the three protocols defined on the two datasets (ROI-1 generated by the sensor during the acquisition and ROI-2 extracted automatically from RAW images by the automatic system).

different subjects. $ii)$ nom L - normal operation mode using just the left hand of the subjects. And $iii)$ nom R - normal operation mode using just the right hand of the subjects. Therefore, nom L&R protocol considers a total of 220 subjects and nom L and nom R a total of 110 subjects. For all the protocols, the enrolment is carried out by using the first two images in the first session and the remaining three images plus the five from the second session comprise the probe.

In each protocol, the database is divided on three different sets: *world/training* (subjects 1-20), *development* (subjects 21-50) and *evaluation* (subjects 51-110) as is described in Table 1. Only the images in *world/training set* should be used to train system components such as world/background models, PCA/LDA subspaces, etc., or to otherwise use as background data, for example for score normalisation, etc. The *development set* only should be used to train system hyper-parameters to minimise the chosen error rate metric. The equal error rate (EER) has been used for this purpose. Finally, the *evaluation set* should be used to evaluate palm vein verification accuracy. The decision threshold was determined by tuning on the *development set* (by using the EER), and then applied to palm vein verification scores produced on the *evaluation set*. The half total error rate (HTER), which is the average of false acceptance and false rejection rates after applying the threshold, has been used to measure that accuracy.

Table 2 and Fig. 3 show the benchmark results for the three protocols on the different sets defined. As we can see the $\mathrm{ROI\text{-}2}$ images produce better results than the $\mathrm{ROI\text{-}1}$ regions, this means that the automatic segmentation implemented align better the palm vein region. Focusing our attention of $\mathrm{ROI\text{-}2}$ results, the system achieved a rate of 3.75% of EER on the development set and 6.80% of HTER on the evaluation set on the nom $\mathrm{L\&R}$ protocol. Results on both hands achieved similar recognition rates of EER on the development set, but however, left hand obtained a rate of 5.90% of HTER on the evaluation set in comparison to the 9.37% of HTER of the right hand. This difference can be explained based on the enrolment images. On the evaluation set of the left hand there are no effects of blurring images, while on the right hand, there are several subjects that experiment this problem on their enrolment images, and therefore, the HTER rate increases.

6 Conclusion

This paper presents a new palm vein database acquired by a contactless sensor together with an open source experimental framework freely available for reproducible research purposes. The scarce number of databases and the unclear protocols proposed so far in the literature of this field make this database a valuable reference for the improvement of palm vein recognition systems. The results obtained so far demonstrate the utility of the database and open the opportunity to research on new approaches in the palm vein pattern recognition field. Therefore, the collected database will be useful for the research community as a reference database that provides replicable and clear analysis protocols and a free experimental framework for the fair reproducible research on the palm vein recognition field.

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