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The Two Sides of the Finger - An Evaluation on the Recognition Performance of Dorsal vs. Palmar Finger-Veins

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Abstract: Vascular pattern (vein) based biometrics, especially finger- and hand-vein recognition gain more and more attention. In finger-vein recognition, the images are usually captured from the palmar (bottom) side of the finger. Dorsal (top) side finger vein recognition has not got much attention so far. In this paper we establish a new, publicly available, two-sided (dorsal and palmar) finger-vein data set. The data set is captured using two custom designed finger vein scanners, one based on near-infrared LED illumination, the other one on near-infrared laser modules. A recognition performance comparison between the single subsets (palmar and dorsal) as well as cross-subset (palmar vs. dorsal) comparison is conducted using several well-established finger-vein recognition schemes. The experimental results confirm that the palmar side achieves the overall best recognition performance but in general the dorsal side works better due to inherent finger texture information.

Keywords: Finger Vein Recognition, Palmar-Dorsal Data Set, Performance Evaluation, Finger Texture Analysis, Finger Vein Scanner Device

1 Introduction

Vein or to be more precise vascular pattern based recognition is an emerging new biometric as it might help to overcome some of the problems existing biometric recognition systems suffer from. Vein based systems rely on the structure of the vascular pattern formed by the blood vessels inside the human body tissue, which becomes visible in near-infrared (NIR) light only. Vein based biometrics are insensitive to abrasion and skin surface conditions. Moreover, a liveness detection can be performed easily [KZ12]. Especially hand- and finger-vein based systems are introduced in commercial systems too. In finger-vein recognition it is common to use the palmar (bottom) side of the finger. The dorsal (top) side of the finger has only got little attention so far. Moreover, it is not clear if the palmar or the dorsal side yields a better recognition performance.

The main contribution of this paper is a new two-side finger-vein data set, comprising dorsal as well as palmar finger-vein images captured from the same subjects. Our data set provides high resolution palmar and dorsal finger-vein images of 360 individual fingers. It contains 4 subsets: one palmar and one dorsal one captured utilising our NIR LED and our NIR laser module based scanner, respectively. Based on these data sets a recognition performance evaluation of both, the palmar and dorsal subsets is conducted in order to answer the question: which side is better in terms of recognition performance - palmar or dorsal? In addition, a cross-comparison experiment between the palmar and dorsal view was done

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to confirm that the vein patters differ and a cross-comparison is not possible. Moreover, a finger texture analysis is conducted in order to quantify the amount of information which is extracted unintentionally from the skin surface texture instead of the vein patterns.

The rest of this paper is organised as follows: Section 2 gives an overview on publicly available finger-vein data sets and related work on dorsal finger-veins, followed by a description of our new two-side, dorsal and palmar, finger vein data set as well as the scanner device. Section 3 outlines the experimental set-up, including the recognition tool-chain as well as the evaluation protocol and presents the performance evaluation results together with a results discussion. Section 4 concludes this paper.

2 Finger-Vein Data Sets

Tab. 1 gives an overview on the 8 publicly available finger vein data sets we found so far. Only one of these data sets includes images that are captured from the dorsal side of the finger, which is the PROTECT Multimodal Database [UoR17]. All the other data sets are captured from the palmar side of the finger. There is some research on dorsal finger-veins, e.g. the work of Raghavendra and Busch [RB15] but their data set has never been published. Heenaye and Khan [HK12] established a dorsal and palmar hand-vein data set and did a score level fusion to improve the overall recognition results. However, they did no direct comparison of the individual performances of palmar and dorsal images. Due to the fact that the vein geometry and properties are different for hand- and finger-veins (finger-veins are smaller and more dense compared to hand-veins), recognition performance results for finger-veins cannot be inferred from hand-veins. To the best of our knowledge there is no work on the direct comparison of palmar and dorsal finger-vein images. Hence, it is not obvious if the palmar or the dorsal side achieves a better recognition performance.

name	subjects	fingers	images	dors/palm	sess.	resolution
UTFVP [TV13]	60	6	1440	palmar	2	672×380
SDUMLA-HMT [YLS11]	106	6	3816	palmar	1	320×240
FV-USM [ASR14]	123	4	5940	palmar	2	640×480
VERA FingerVein [TVM14]	110	2	440	palmar	2	665×250
MMCBNU_6000 [Lu13]	100	6	6000	palmar	1	640×480
THU-FVFDT [YYL09]	610	2	6540	palmar	2	720×576
HKPU-FID [KZ12]	156	2	3132	palmar	2	512×256
PMMDB-FV [UoR17]	20	4	240	dorsal	1	1280×440

Tab. 1: Overview on publicly available finger-vein data sets. Note: only one contains dorsal images.

2.1 PLUSVein Dorsal-Palmar Finger-Vein Data Set

Our PLUSVein Dorsal-Palmar finger-vein data set was acquired with our two custom designed finger vein scanners, an NIR LED and a NIR laser module based version, which are depicted in Fig. 1. The scanners are designed to capture 3 fingers (index, middle and ring finger) at once. Both scanners are based on an NIR enhanced industrial camera equipped with a 9 mm lens in combination with an NIR pass-through filter. Its main light source is

a transillumination one consisting of 3 stripes (one underneath each finger) of NIR LEDs for the LED version or NIR laser modules for the laser version of the scanner, respectively. Each LED/laser module is brightness controlled individually and automatically based on a preset brightness value to achieve an optimal image contrast. An LED ring consisting of 8 850 nm LEDs, 8 950 nm LEDs and 8 daylight LEDs for capturing reflected light images is situated on top of the device and can be automatically brightness controlled too. To assist in positioning of the finger, the lower part contains a custom 3D printed finger support which also serves as a bracket for the 3 illumination stripes.

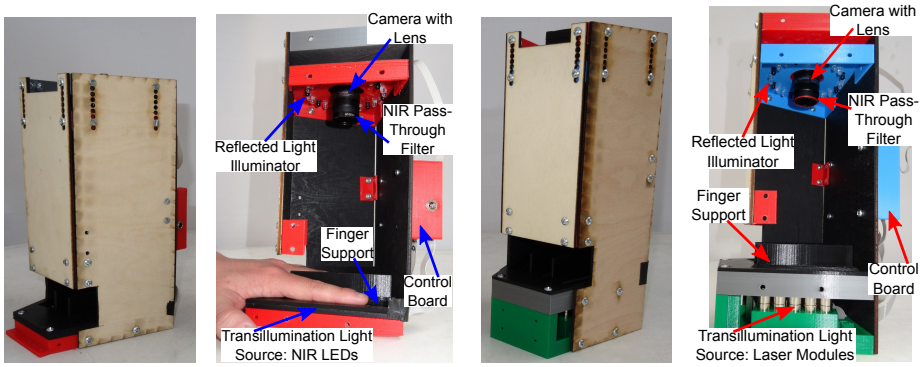

Fig. 1: Left: LED based finger-vein scanner, right: laser module based finger vein scanner

The finger-vein data set itself consists of 4 subsets: one dorsal and one palmar finger-vein subset captured using transillumination with the LED and the laser module based scanner, respectively. 60 subjects, 6 fingers (left and right index, middle and ring finger) and 5 images per finger in 1 session were captured for each of the four subsets. So each subset consists of the same 360 individual fingers but captured from a different view - palmar for the first two and dorsal for the second two. Each scanner captures 3 fingers at a time. Thus, each subset contains 600 raw finger-vein images. Some example images can be seen in Fig. 2. The images are then separated into 3 parts, corresponding to index, middle and ring finger, respectively. Hence, there are effectively 1800 images in each subset and 7200 images in total for the whole data set. The raw images have a resolution of 1280×1024 pixels and are stored in 8 bit greyscale png format. The finger separated images have a resolution of 420×1024 pixels and the visible area of the finger inside the images is about 200×750 pixels per finger. The data set is publicly available for research purposes and can be downloaded at: `http://www.wavelab.at/sources/PLUSVein-FV3/`.

3 Experiments

The finger-vein processing tool-chain consists of ROI (region of interest) extraction, preprocessing, feature extraction and comparison. At first the input image is split into 3 parts based on fixed coordinates, corresponding to index, middle and ring finger, respectively. From here on each image is processed individually. The ROI is extracted by first detecting the finger outline. Then the area outside the finger is masked out (pixels set to black). Afterwards, the finger is aligned (rotated and shifted) such that it is in upright position in

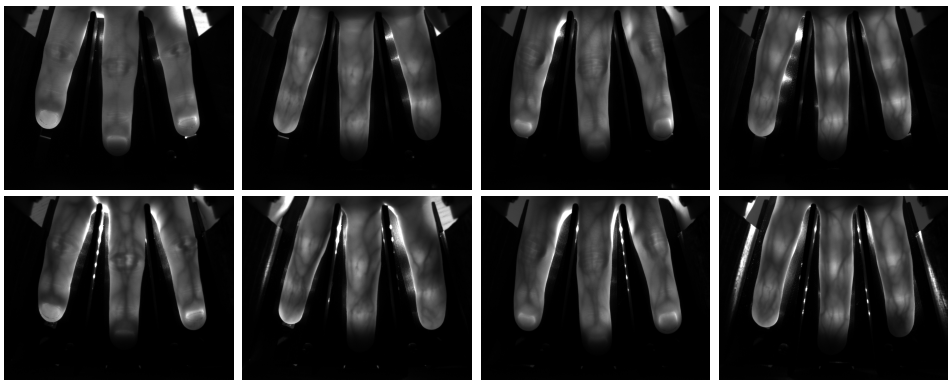

Fig. 2: Finger-vein example images captured by our three finger vein scanners, top: laser scanner, bottom: LED scanner, first and third column: dorsal, second and fourth column: palmar

the centre of the image based on a straight centre line which is fitted into the finger and a rectangular ROI is fit inside the finger area. The ROI images have a size of 192×736 pixels. To improve the visibility of the vein pattern we employ **High Frequency Emphasis Filtering** (HFE), **Circular Gabor Filter** (CGF) and simple **CLAHE** (local histogram equalisation) as preprocessing. We opted for three well-established binarisation type feature extraction methods as well as one **SIFT** key-point based method (SIFT) with additional key-point filtering. **Maximum Curvature** (MC) [MNM07], **Principal Curvature** (PC) [Ch09] and **Gabor Filter** (GF) [KZ12] aim to extract the vein pattern from the background resulting in a binary image, followed by a comparison of these binary images. Comparing the binary feature images is done using template matching as suggested by Miura et al. [MNM07]: The maximum correlation value, calculated between the input images and in x- and y-direction shifted and rotated versions of the reference image is used as comparison score. For more details on the preprocessing, feature extraction and comparison methods please refer to [KRU14].

The EER as well as the FMR1000 (the lowest $FNMR$ for $FMR \leq 0.1\%$) and the ZeroFMR (the lowest $FNMR$ for $FMR = 0\%$) are used to quantify the performance. All possible genuine comparisons are performed, which are $60 \cdot 6 \cdot \frac{5 \cdot 4}{2} = 3600$ comparisons, while for the impostor comparisons only the first image of each finger is compared against the first image of all other fingers, resulting in $\frac{60 \cdot 6 \cdot (60 \cdot 6 - 1)}{2} = 64620$ impostor comparisons and68220 comparisons in total. All result values are given in percentage terms, e.g. 2.78 means 2.78%. An implementation of the complete processing tool-chain as well as the scores and detailed results are available at: `http://www.wavelab.at/sources/Kauba18d/`.

3.1 Single Subset Results

Tab. 2 lists the recognition performance in terms of EER (the value in brackets is the 90% confidence interval), FMR1000 and ZeroFMR for both data sets, the LED and the laser

scanner one. The DET plots are depicted in Fig. 3. The same settings per recognition scheme have been used for both subsets: dorsal/palmar but different ones for laser and LED. For the LED palmar subset MC performed best, achieving an EER of 0.06%, followed by PC and SIFT while GF performed worst. For the dorsal subset the situation is different: This time SIFT performed best with an EER of 0.06%, followed by PC and MC while GF achieved the worst performance. All schemes perform slightly worse on the laser scanner data set, with MC achieving the best overall EER of 0.11% on the palmar sub set, except for GF on laser palmar which is superior to the LED palmar sub set. The table reveals that only MC performs better for palmar finger-vein images. PC, SIFT and GF perform better on the dorsal subset. Especially SIFT and GF perform much better on dorsal than palmar images. The FMR1000 and ZeroFMR results follow the same trend as the EER ones.

		Dorsal			Palmar		
		EER	FMR1000	ZeroFMR	EER	FMR1000	ZeroFMR
LED	MC	0.17 (±0.07)	0.19	0.22	**0.06** (±0.04)	**0.03**	**0.19**
	PC	0.11 (±0.06)	0.11	**0.11**	0.17 (±0.07)	0.19	0.64
	SIFT	**0.06** (±0.04)	**0.06**	0.28	0.64 (±0.13)	1.67	3.83
	GF	0.25 (±0.08)	0.28	0.75	1.42 (±0.2)	2.36	6.64
Laser	MC	0.2 (±0.07)	0.28	**0.64**	**0.11** (±0.06)	**0.11**	**0.33**
	PC	0.44 (±0.11)	0.53	1.14	0.48 (±0.11)	0.69	0.97
	SIFT	**0.13** (±0.06)	**0.17**	0.89	1.25 (±0.19)	3.0	6.44
	GF	0.64 (±0.14)	0.81	1.5	1.19 (±0.18)	2.17	3.92

Tab. 2: Recognition performance results, dorsal and palmar for both data sets (LED + laser), best results per side and scanner are highlighted **bold**

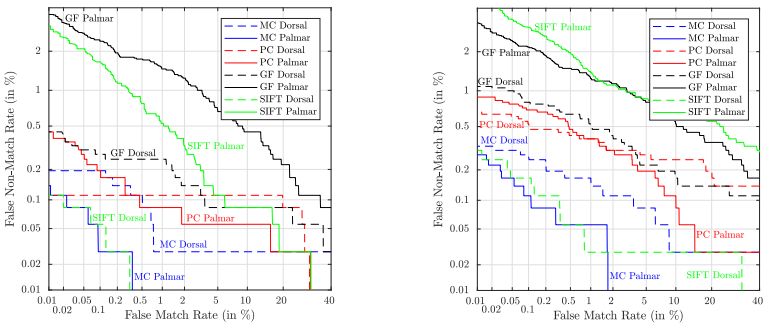

Fig. 3: DET plots: LED based scanner (left) and laser based scanner (right)

3.2 Dorsal-Palmar Cross-Comparison Results

By applying transillumination only the veins which are close to the finger skin become visible as discussed in [MNM04] and [Ko00]. As these surface vein patterns on the palmar and dorsal side of the finger differ [GG74], a cross comparison between palmar and dorsal images will not be possible. For the sake of completness we performed a cross comparison between the palmar and flipped dorsal (palmar images have been captured by turning the finger 180° around its axis) images. The results given in Tab. 3 confirm that that a cross-

comparison between dorsal and palmar images of the same fingers is not possible (EER around 50%, FMR1000 and ZeroFMR nearly 100%).

	LED				Laser			
	MC	PC	SIFT	GF	MC	PC	SIFT	GF
EER	47	50	47	49	49	50	46	48
FMR1000	99	99	99	99	99	99	99	99
ZeroFMR	99	99	100	100	100	100	100	100

Tab. 3: Cross-comparison (palmar vs. dorsal) results for both data sets (LED + laser). The values indicate that a comparison between dorsal and palmar is not possible

3.3 Finger Texture Analysis

Fig. 4 shows a comparison of the extracted features for MC and GF on palmar and dorsal LED scanner images, respectively. There is some finger surface texture visible in both, the palmar and dorsal images, but it is more pronounced in the dorsal ones. Especially GF does not only extract vein lines, but also the wrinkles and the finger texture. Also SIFT, as a general purpose key-point descriptor uses the additional information present due to the finger texture. On the other hand, MC tries to suppress the non-vein texture and therefore mainly relies on the vein lines. It shows less extracted features that actually belong to the finger texture instead of vein lines than GF. To quantify the amount of finger texture and wrinkle information present in the extracted vein features we rely on the three binarisation type feature extractors (MC, PC and GF) and perform an edge detection based analysis: Most finger vein lines are apparent as horizontal lines while the finger texture and wrinkles are usually apparent as vertical lines. Thus, vertical edges correspond to finger texture information whereas horizontal edges correspond to vein lines, respectively. We apply a Prewitt filter based edge detection to detect vertical and horizontal edges separately and quantify the amount of edge information: $e = \frac{p_e}{w \cdot h}$ where e is the amount of edge information in the image, p_e are the detected edge pixels and w, h is the image width and height, respectively. Afterwards, the ratio between vertical and total edges is used to predict the amount of finger texture information present in the images: $fti = \frac{e_v}{e_h}$, where e_v and e_h is the vertical and horizontal edge information, respectively. Higher values of fti correspond to a higher amount of finger texture information present. Tab. 4 shows these values for MC, PC and GF based on the LED scanner images (SIFT does not produce binary output images). For all 3 feature extraction schemes the finger texture information present in the dorsal feature images is higher than in the palmar ones (1.369 times for MC, 1.281 for PC and 1.752 for GF). This additional features originating from the finger texture help in discriminating between different fingers and thus increase the recognition performance. Consequently PC, GF and SIFT perform better for the dorsal images due to the additional finger texture information compared to the palmar images.

4 Conclusion

We established a new dorsal and palmar finger-vein data set, containing 7200 images from 360 different fingers, captured with two different custom designed scanners, an LED based one and a laser module based one. Based on this data set we did a direct comparison of

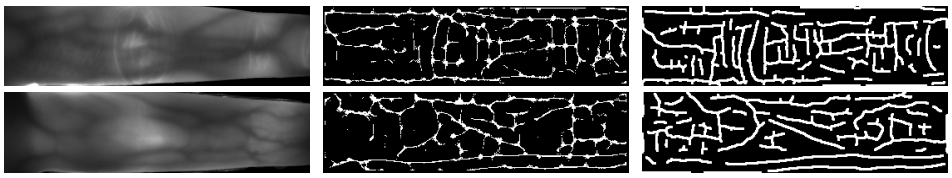

Fig. 4: Comparison between dorsal (top) and palmar (bottom) extracted features for MC (middle) and GF (right). The dorsal images show more finger texture (vertical lines) especially for GF compared to the palmar ones.

	Dorsal			Palmar			Dorsal/Palmar
	e_v	e_h	fti	e_v	e_h	fti	fti_D/fti_P
MC	0.0134	0.0203	0.6737	0.0104	0.0213	0.4918	1.369
PC	0.0139	0.0174	0.8013	0.0109	0.0176	0.6255	1.281
GF	0.0158	0.0189	0.8627	0.0138	0.0233	0.4571	1.752

Tab. 4: Finger texture information contained in the dorsal and palmar LED scanner images quantified in terms of horizontal and vertical edges. Higher values of fti correspond to more finger texture information present.

palmar and dorsal finger-vein images in terms of recognition performance using several well-established recognition schemes. The experimental results reveal that the overall best performance is achieved for palmar images. Although, in general the dorsal images perform better than the palmar ones, mainly due to the fact that not only the vein lines are extracted during feature extraction, but also the finger texture and wrinkles are considered. The dorsal images show more texture information than the palmar ones and consequently, most of the tested recognition schemes work better using the dorsal images. Moreover, our results confirmed that a cross-comparison between palmar and dorsal vein patterns is not possible.

Our future work will include tests with some more state-of-the-art finger-vein recognition schemes. Moreover, we are going to design a suitable preprocessing method to suppress the finger texture information and wrinkles in order to have the extracted features based on vein lines only and thus to make the results independent from the finger texture information. After all, vein recognition should only deal with vascular pattern information and not the skin surface texture one.

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