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Shedding Light on the Veins - Reflected Light or Transillumination in Hand-Vein Recognition

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Abstract

The near-infrared light source is a crucial part of a hand-vein scanner. Depending on its position there are two main illumination types: reflected light and transillumination. Commercial scanners and all publicly available data sets use reflected light. We established two dual illumination dorsal hand-vein data sets (one of them is made publicly available) including both, reflected light and transillumination images acquired using the same subjects, hand position and environmental conditions. This enables a direct comparison of both illumination scenarios as well as cross-illumination matching. Several experiments utilising common hand-vein recognition algorithms were carried out to quantify the recognition performance in each of the illumination scenarios and in the cross-illumination matching one.

1. Introduction

Biometric authentication systems are well established today as they exhibit many advantages over traditional password and token based ones. The most prominent examples are fingerprint and face recognition systems. In recent times, authentication based on finger- and hand-veins gains more attention as it provides advantages over the well established fingerprint ones. Hand-vein recognition utilises the pattern of the blood vessels inside the hand of a human, which is captured using near-infrared (NIR) illumination. The vein patterns are neither susceptible to abrasion nor to skin surface conditions. However, hand-vein based systems need relatively big capturing devices compared to fingerprint sensors, the vein images have low contrast and quality in general and the vein structure may be influenced by temperature, physical activity and certain injuries and diseases.

NIR illumination is the key to finger- and hand-vein recognition. The positioning of the light source with respect to the camera and the subject's finger or hand plays an important role. We distinguish between reflected light, where the light source and the camera are placed on the same side of the hand and transillumination, where the light source and the camera are located on the opposite side of the hand. In hand-vein recognition all of the publicly available data sets use reflected light illumination [1, 3, 8, 17, 6]. Some authors used transillumination [20, 16], however their data sets are not available. Furthermore, all commercial hand-vein scanners are based on reflected light. To the best of our knowledge there is no direct comparison of transillumination and reflected light in terms of recognition performance (requiring a data set containing both illumination conditions). Moreover, it is not clear if cross matching between reflected light and transillumination data is feasible.

The main goal of this work is to shed some light on these two different illumination types. We established one in-house and one publicly available dual illumination dorsal hand vein data set, both containing images acquired utilising reflected light (one of them with two different wavelengths, 850 nm and 950 nm) and transillumination of the same subjects. The hand remained in the same position during capturing of the different illumination conditions. Based on these data sets the individual performances of several hand-vein recognition algorithms are evaluated and compared with respect to reflected light and transillumination. The second set of experiments is devoted to cross matching scenarios, reflected light - transillumination as well as reflected light 850 nm - reflected light 950 nm in order to assess the practical feasibility of cross-illumination matching. Based on the results we give an explanation why cross-illumination matching cannot work straight forward using simple vein feature extraction methods.

The rest of this paper is organised as follows: Section 2 gives an overview of hand-vein recognition. At first the principle of the acquisition hardware is explained, including the different types of illumination, followed by a summary of available hand-vein data sets. Then a brief overview of the evaluated preprocessing, feature extraction and matching methods is given. Section 3 describes the two data sets and the scanner hardware used during the acquisition. Sec-

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tion 4 outlines the experimental set-up, lists and discusses the results. Section 5 concludes this paper.

2. Hand Vein Recognition

Hand-vein recognition cannot be done without capturing the biometric trait, i.e. the vein patterns, using an appropriate scanner. A hand-vein scanner consists of 2 basic components: a NIR sensitive camera and a NIR light source. Usually there is some automatic illumination intensity control to achieve an optimal contrast of the vein images. The wavelength of the NIR light source is between 730 and 950 nm as this NIR light is absorbed by the haemoglobin in the blood flowing through the veins and arteries. Thus, they appear as dark lines in the captured images. The camera should be equipped with an IR pass-through filter to block the ambient light and further enhance the image contrast.

2.1. Illumination Types

Two main illumination types are distinguished: reflected light and transillumination. Figure 1 shows the positioning for both illumination types. For reflected light, the light source and the camera are positioned on the same side of the hand, either palmar or dorsal. The light originates from the light source, gets reflected at the hand's surface and tissue and is captured by the camera. Usually images are taken from the palmar part. All commercial available hand-vein scanners (Fujitsu, Sensometrix) are using reflected light. They can be built as small as fingerprint scanners, but are more sensitive to ambient light as well as dirt and e.g. sun lotion on the hand surface. In the transillumination setting the light source and the camera are placed on opposite sides of the hand. The light penetrates the skin and tissue of the hand and gets captured by the camera afterwards. Ttransillumination requires a higher light intensity than reflected light and the whole scanner device is bigger (due to the opposite positioning). But usually more of the small, thin veins are visible and the influence of ambient light and hand surface conditions is reduced. In contrast to commercial hand-vein scanners, most commercial available finger-vein scanners (Hitachi) are based on the transillumination principle, which can be built more compact than the hand-vein ones and achieve better performance at finger-veins than reflected light.

2.2. Public Datasets

Table 1 provides an overview of the publicly available hand-vein data sets. All of these data sets use reflected light illumination.

2.3. Preprocessing, Feature Extraction and Matching

The hand-vein recognition toolchain consists of preprocessing, feature extraction and matching. We opted for simple binarisation type feature extraction methods as their output feature images can be compared visually. Thus, they are more suitable to highlight the differences across the illumination scenarios in the figures. In addition, we included a key-point based method (SIFT based) to have a complimentary feature type too. Implementations of all of the methods we used are publicly available.

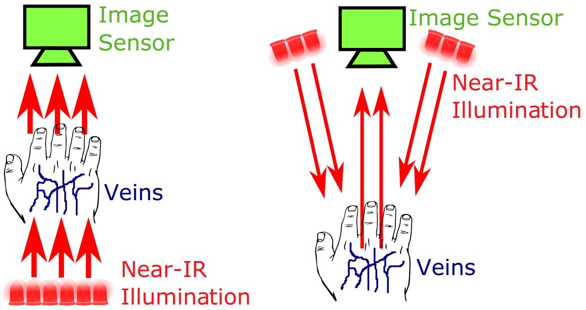

Figure 1. Transillumination (left) and reflected light illumination (right) principle.

Preprocessing tries to enhance the low contrast and improve the image quality. We applied **CLAHE** [22], which is the most prevalent and simple technique, as well as **High Frequency Emphasis Filtering (HFE)**, which was proposed especially for hand vein image enhancement [21]. In addition, filtering using a **Circular Gabor Filter** (**CGF**) as proposed by Zhang and Yang [19] was utilised. Furthermore, the images were resized to half of its original size, which not only speeded up the matching process but further improved the results due to intrinsic denoising. For more details on the preprocessing and feature extraction methods the interested reader is referred to [9].

Feature Extraction and Matching The methods we used were originally proposed for finger vein recognition but have been successfully applied in hand-vein recognition too [10]. The first three of the following techniques aim to extract the vein pattern from the background resulting in a binary template image followed by a comparison of these binary templates using a correlation measure.

Maximum Curvature (MC [15]) aims to emphasise only the centre lines of the veins, making it insensitive to varying vein widths. The first step is the extraction of the centre positions of the veins. Afterwards a score according to the width and curvature of the vein region is assigned to each centre position and recorded in a matrix called locus space. Due to noise or other distortions some pixels may not have been classified correctly at the first step, thus the centre positions of the veins are connected using a filtering operation. Finally binarisation is done by thresholding using the median of the locus space.

Name	Images	Subjects	Imgs/ hand/ session	Dorsal/palmar	Resolution	Illumin. type	Camera type
CIE [8]	2400	50	12	palmar and wrist	1280 × 960	reflected light	low cost USB camera
Vera Palm Vein [17]	2200	110	5	palmar	580 × 680	reflected light	-
Bosphorus Hand Vein [1]	1575	100	3	dorsal	300 × 240	reflected light	monochrome NIR CCD camera
CASIA Multispectral [6]	7200	100	18	palmar	660 × 550	reflected light	multi-spectral imaging device
Tecnocampus Hand Image [3]	6000	100	12	palmar and dorsal	640 × 480	reflected light	NIR, visible light and thermal

Table 1. Publicly available hand-vein data sets

Principal Curvature (PC [2]): At first the gradient field of the image is calculated. Hard thresholding is done to filter out small noise components and then the gradient at each pixel is normalised to 1 to get a normalised gradient field. This is smoothed by applying a Gaussian filter. The next step is the actual principal curvature calculation, obtained from the Eigenvalues of the Hessian matrix at each pixel. Only the bigger Eigenvalue, corresponding to the maximum curvature, is used. The last step is a binarisation of the principal curvature values to get the binary vein output image.

Gabor Filter (GF [11]): The image is filtered using a filter bank consisting of several 2D even symmetric Gabor filters with different orientations, resulting in several feature images. The final vein feature image is obtained by fusing all these single images, which is then post-processed using morphological operations to remove noise.

For matching the binary feature images we adopted the approach of Miura et al. [15]. As the input images are neither registered to each other nor aligned, the correlation between the input image and x- and y-direction shifted versions of the reference image is calculated. The maximum of these correlation values is normalised and then used as final matching score. Hand-vein images, especially ROI images, cannot be rotationally aligned like finger vein images (based on the finger outline), so we had to account for differently rotated images. Our main focus is on matching performance and not on runtime. Thus, the rotation correction is simply done by matching the template image against rotated versions (steps of $0.5°$ in a range of $\pm 15°$) of the probe image and again using the maximum score as final matching score.

In contrast to the techniques described above, key-point based techniques try to use information from the most discriminative points as well as considering the neighbourhood and context information of these points by extracting key-points and assigning a descriptor to each key-point. We used a **SIFT** [12] based technique with additional key-point filtering as proposed by Kauba et al. [9].

3. Dual Illumination Hand-Vein Data Sets

In this section we describe our two dual illumination (reflected light and transillumination) hand-vein data sets.

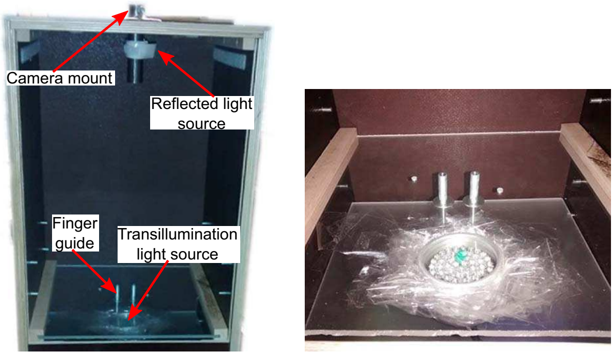

Figure 2. Hand-vein scanner for VeinPLUS (left) and a detail of the surface where the hand is placed including the light source for transillumination (right).

VeinPLUS [4]: The scanner used for capturing the **VeinPLUS** data set consists of a modified Canon EOS 5D MarkII DSLR (removed IR-blocking filter) with an additional 830 nm IR pass-through filter, mounted on the top of the scanner box. There are two NIR LED light sources, one for transillumination using a NIR surveillance lamp with 50 940 nm LEDs, mounted below a glass plate, and 6 950 nm NIR LEDs mounted on top of the wooden box for reflected light. The hand is placed on top of the glass plate above the transillumination light source (see Figure 2).

The data set consists of 107 subjects, 2 hands per subject for most of the subjects, at least 3 images per hand and 2 illumination settings per hand, resulting in a total of 1213 RGB colour dorsal hand-vein images with a resolution of 2784 × 1856 pixels. The extracted ROIs are 500 × 500 pixels. More details about the scanner and the database can be found in [4]. Figure 3 shows some example images.

PROTECT Multimodal Biometric Data Set [18]: The hand-vein data set included in the PROTECT Multimodal Biometric Database (**PROTECTVein**) was acquired using a custom built scanner shown in Figure 4. This scanner uses two imaging devices. The first one is a NIR enhanced industrial camera (IDS Imaging UI-1240ML-NIR, max. resolution 1280x1024 pixels) together with a 9 mm wide-angle-

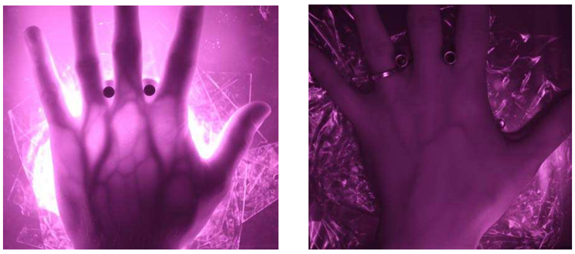

Figure 3. Example images of the the VeinPLUS data set. Left: transillumination, right: reflected light.

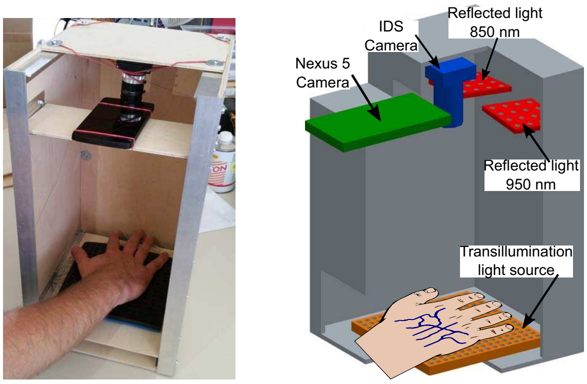

Figure 4. Hand-vein scanner for PROTECTVein. Left: actual hardware, right: schematic diagram of the set-up.

lens. The second one is a modified Nexus 5 smartphone (by EigenImaging), which has its IR-blocking filter removed but has no additional IR pass-through filter, max. resolution 3264x2448 pixels. The scanner has 4 different light sources. A 16x16 NIR LED matrix (850 nm LEDs) at the bottom for transillumination, where the brightness of each LED can be controlled separately and two intensity controllable 4x4 NIR LED panels at the top, one using 850 nm LEDs and the other one using 950 nm LEDs, both dedicated to reflected light. In addition, there are 2 3x3 LED panels consisting of white LEDs to support the Nexus 5 at focusing. Thus, 3 different illumination scenarios and 2 capturing devices are available, resulting in 6 different sub data sets.

This data set consists of 40 users, both hands, 5 images per hand (each time removing the hand from the device and putting it in again) and 3 illumination types captured with both cameras in one session, resulting in $40 \cdot 2 \cdot 5 = 400$ dorsal hand-vein images per subset and $400 \cdot 3 \cdot 2 = 2400$ images in total. The hand remained in the same position while capturing all 6 different camera/illumination conditions. The images captured with the IDS camera are greyscale with a resolution of 720×720 pixels. The Nexus 5 images are RGB, 3264×2448 pixels. Figure 5 shows some example images. The ROI was extracted manually. The ROI images have a size of 384×384 pixels for the IDS camera and 704×704 for the Nexus 5.

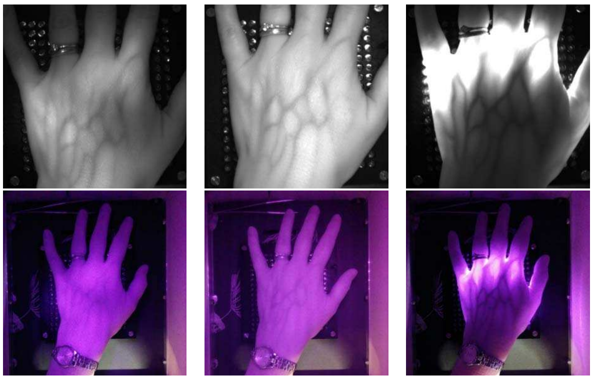

Figure 5. Example images of the PROTECTVein data set. First row showing the images captured with the IDS camera (from left to right: reflected light 850 nm, reflected light 950 nm, transillumination), second row showing the Nexus 5 images.

Due to legal issues we are not allowed to publish the PLUSVein data set as the original consent form does not include the right to publish the acquired hand vein images. The PROTECTVein data set is publicly available and can be downloaded at: `http://projectprotect.eu/dataset/`.

4. Experiments

The experiments are split into two main parts: The first part deals with the performance evaluation of each single data set in order to compare the performance of reflected light versus transillumination. The second part deals with the cross matching performance between the three different illumination scenarios. To quantify the performance, the EER as well as the FMR1000 (the lowest $FNMR$ for $FMR <= 0.1\%$) and the ZeroFMR (the lowest $FNMR$ for $FMR = 0\%$) are used. For their calculation we followed the test protocol of the FVC2004 [13]. Only the ROI images of both data sets were used. All values are given in percentage terms, e.g. 2.35 means 2.35%. An implementation of our complete toolchain as well as the performance evaluation score sets are available at: `http://www.wavelab.at/sources/Kauba18a/`.

4.1. Single illumination/spectrum results

Table 2 lists the results for the VeinPLUS data set. MC using transillumination achieves the best performance in terms of EER (0.255%) as well as FMR1000 and ZeroFMR, followed by PC, then by GF and SIFT performing worst. For VeinPLUS reflected light leads to an inferior recognition performance compared to transillumination in general.

The results for the first subset (IDS camera) of the PROTECTVein data set are given in Table 3. In general MC performs best, followed by GF and PC while SIFT performs worst, except for reflected light 950 nm, where it performs best with an EER as low as 0.093%. This is due to the vis-

		MC	PC	SIFT	GF
Transillum.	EER [%]	0.255	0.329	0.979	0.411
	FMR1000 [%]	0.41	0.329	5.164	0.411
	ZeroFMR [%]	0.574	0.656	8.852	0.411
Refl. Light	EER [%]	0.969	0.788	1.402	3.047
	FMR1000 [%]	1.655	0.958	4.268	4.53
	ZeroFMR [%]	2.885	2.0	5.923	6.36

Table 2. VeinPLUS recognition performance results

		MC	PC	SIFT	GF
Transillum.	EER [%]	1.496	3.741	4.707	1.621
	FMR1000 [%]	2.114	15.79	12.94	1.866
	ZeroFMR [%]	2.239	19.65	12.94	1.866
Reflected 850	EER [%]	0.253	0.253	3.377	0.253
	FMR1000 [%]	0.254	0.373	8.085	0.373
	ZeroFMR [%]	0.254	0.373	8.582	0.746
Reflected 950	EER [%]	0.124	0.373	0.093	0.249
	FMR1000 [%]	0.248	0.373	0.1	0.371
	ZeroFMR [%]	0.248	0.373	0.495	0.495

Table 3. PROTECTVein IDS recognition performance results

		MC	PC	SIFT	GF
Transillumination	EER [%]	3.134	2.759	7.899	26.77
	FMR1000 [%]	17.73	5.535	24.91	59.25
	ZeroFMR [%]	19.75	7.925	29.43	59.75
Reflected Light 850	EER [%]	5.41	3.752	19.61	34.65
	FMR1000 [%]	12.39	14.64	54.19	78.6
	ZeroFMR [%]	15.27	16.9	60.58	81.85
Reflected Light 950	EER [%]	6.572	8.113	12.14	40.88
	FMR1000 [%]	30.13	26.71	44.68	89.87
	ZeroFMR [%]	30.5	31.27	53.92	92.03

Table 4. PROTECTVein Nexus 5 recognition performance results

ibility of both, the vein pattern and detailed skin texture of the hand surface in the images. SIFT extracts keypoints and information from all the visible texture, thus there is more distinguishable information in this case, which increases its recognition performance. MC achieves the best recognition performance using reflected light 950 nm with an EER of 0.124%. Reflected light 850 nm performs better when using GF but not for the other recognition schemes. This time transillumination performs by far worse than both reflected light illumination scenarios, which is in contrast to the VeinPLUS results, where transillumination outperformed reflected light. See Section 4.3 for a discussion on this finding.

Table 4 lists the results for the second subset (Nexus 5 Smartphone) of the PROTECTVein data set. Compared to the first subset (IDS camera), the recognition performance is clearly inferior. The Nexus 5 camera has its IR blocking filter removed but is not especially designed for NIR light, i.e. the higher the wavelength the lower the sensitivity. Thus, reflected light 950 nm performs worst, followed by reflected light 850 nm. Transillumination works best, simply due to the higher light intensity. PC performs best (except for reflected light 950 nm), followed by MC and SIFT. GF performs by far worst for the Nexus 5 images.

	MC	PC	SIFT	GF
EER [%]	49.47	49.98	55.79	55.96
FMR1000 [%]	99.29	99.91	99.91	99.55
ZeroFMR [%]	99.91	99.91	99.91	99.64

Table 5. VeinPLUS reflected light against transillumination matching recognition performance results

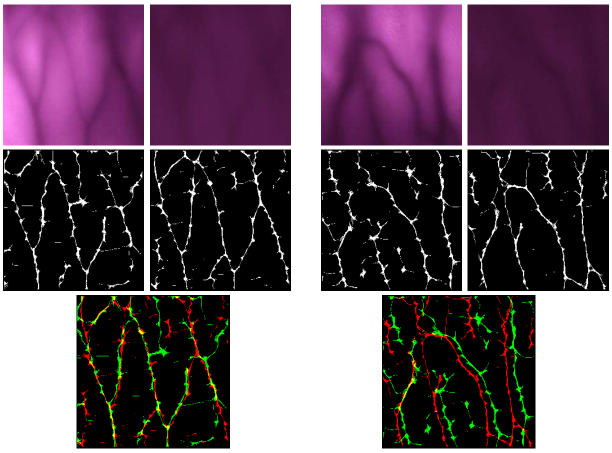

Figure 6. Two example comparisons (left part and right part) between reflected light (top right) and transillumination (top left) for VeinPLUS. The second row shows the corresponding MC feature extraction and the third row an overlay of both (green is transillumination, red is reflected light).

4.2. Cross-spectrum and cross-illumination results

Table 5 shows the cross-illumination matching results for VeinPLUS. The EER values are around 50% or even above and the FMR1000/ZeroFMR are almost 100%. This clearly points out that cross-illumination matching between transillumination and reflected light is not possible, at least not in a straightforward manner.

The cross-illumination matching results for the IDS camera sub set of PROTECTVein are listed in Table 6. MC and PC perform well for reflected light 850 nm against reflected light 950 nm. Thus cross-spectrum matching between the different wavelengths of reflected light is possible. SIFT does not perform well, i.e. it is not suitable for cross-spectrum matching in this case. The performance for transillumination - reflected light is more than 50 times worse than for reflected light, indicating that again cross-illumination matching is not feasible in this case.

The results for the Nexus 5 subset of the PROTECTVein data set in Table 7 are in line with the ones for the IDS camera subset meaning that cross-illumination matching performs worse compared to the single illumination one in each test case.

4.3. Results Discussion

The hand-vein specific feature extraction methods (MC and PC) outperformed the more general purpose SIFT ap-

		MC	PC	SIFT	GF
Trans. - Ref. 850	EER [%]	7.61	23.32	46.49	14.08
	FMR1000 [%]	40.72	81.69	99.75	49.07
	ZeroFMR [%]	58.41	87.17	99.86	50.81
Trans. - Ref. 950	EER [%]	8.58	19.06	43.35	13.66
	FMR1000 [%]	33.25	63.14	99.88	40.35
	ZeroFMR [%]	39.1	65.13	99.88	54.17
Ref. 850 - Ref. 950	EER [%]	0.593	3.37	34.11	0.874
	FMR1000 [%]	1.733	8.787	96.78	1.98
	ZeroFMR [%]	1.856	9.9	98.51	3.094

Table 6. PROTECTVein cross-illumination matching IDS results

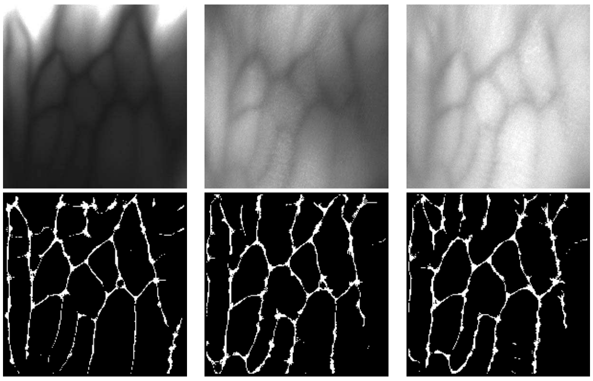

Figure 7. Example comparison 1 between transillumination (left), reflected light 850 (middle) and reflected light 950 (right) for PROTECTVein. The first row shows the ROI images, the second row the corresponding MC feature extraction images. Basically the same veins are visible in the MC feature images, but there are not in the exact same positions (see Figure 9).

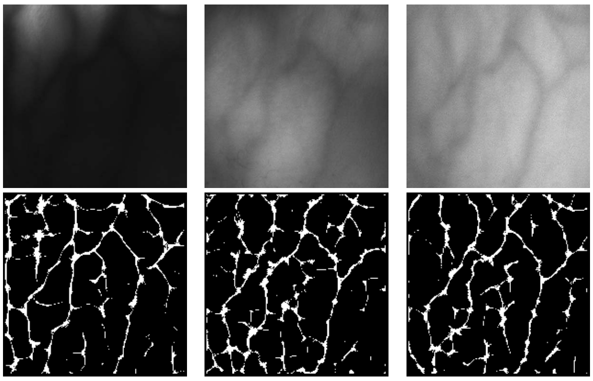

Figure 8. Example comparison 2 between transillumination and reflected light for PROTECTVein. Cf. Figure 7.

proach. They steadily exhibit good recognition rates in terms of EER/FMR1000/ZeroFMR across the different illumination settings and sensors except for the Nexus 5 sensor.

Image sensor The modified Nexus 5 smartphone is not able to keep up with industrial NIR enhanced cameras. It achieved a significantly lower recognition performance compared to the IDS camera.

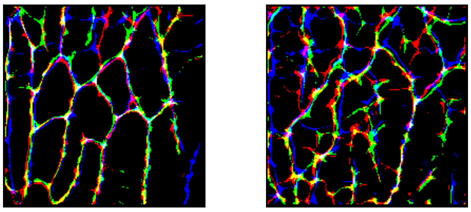

Figure 9. MC features overlay for Figure 7 (left) and 8 (right). Red is reflected light 850 nm, green is reflected light 950 nm and blue is transillumination. For example subject 1 there is only little displacement between the different illuminations while there is more displacement for example subject 2.

		MC	PC	SIFT	GF
Trans. - Ref. 850	EER [%]	20.5	23.34	48.13	48.97
	FMR1000 [%]	57.86	72.7	99.5	99.62
	ZeroFMR [%]	59.12	80.0	99.85	99.74
Trans. - Ref. 950	EER [%]	19.12	23.3	49.97	45.72
	FMR1000 [%]	59.62	78.35	99.87	98.61
	ZeroFMR [%]	62.15	83.04	99.87	99.37
Ref. 850 - Ref. 950	EER [%]	13.2	13.2	49.41	46.18
	FMR1000 [%]	37.74	42.77	99.87	96.86
	ZeroFMR [%]	41.76	58.99	99.87	97.48

Table 7. PROTECTVein cross-illumination matching Nexus 5 results

Reflected light 850 nm vs. 950 nm The PROTECTVein data set results confirm that 950 nm improves the performance compared to 850 nm reflected light if the camera is a dedicated NIR one (improvement for the IDS subset but not for the Nexus 5 one).

Reflected light vs. transillumination Concerning the PROTECTVein IDS camera subset, transillumination achieved a lower performance than reflected light due to the following reasons: In contrast to the VeinPLUS scanner, which has a diffuse illuminator directed at the inside walls of the box with fixed light intensity only, the reflected light illuminator of the PROTECTVein scanner is directed at the hand surface and has an automatic intensity control, which improves the illumination. Second, transillumination needs a high light intensity to shine through the whole hand. The light intensity of the NIR LED board was not high enough to shine through some thicker hands, which can be seen in the images (the lower parts are almost dark) in top left of Figure 7 and 8. Analysing the images of the PROTECTVein IDS subset using 3 image contrast metrics, GCF [14], and two information entropy based ones GLES (Grey Level Entropy Score) and ES (Entropy Score) (section 5.1 and 2.4 in [5])) (see Table 8 for the results), reveals that the reflected light images exhibit higher image contrast and quality than the transillumination ones. Therefore, reflected light, especially the 950 nm one is favourable in the PROTECTVein set-up. However, transillumination achieved better results then reflected light for VeinPLUS which is supported by the

		GCF	GLES	ES
PROTECTVein IDS	Refl. 850	2.211	0.991	7.015
	Refl. 950	2.8	0.988	6.57
	Transillum.	1.889	0.959	6.004
VeinPLUS	Refl. light	0.358	0.891	3.461
	Transillum.	1.392	0.989	6.869

Table 8. Image quality metric results. GCF values are in the range of [0, 8], GLES values are in the range of [0, 1] and ES values are in the range of [0, 8]. Higher values correspond to higher image contrast.

image contrast metrics as the transillumination images have higher metrics scores.

In general, transillumination is more robust against hand surface conditions and the influence of ambient light, but requires a higher light intensity compared to reflected light, thus consuming more power. Due to the illuminant positioning on the opposite side of the camera, hand-vein sensors based on transillumination are bigger and not suitable for mobile application.

Reflected light requires much lower light intensities than transillumination and consequently consumes less power, which is important for battery operated devices. The main advantage of reflected light is that it enables a smaller design of the overall hand-vein sensor. Due to the lower light intensities, a reflected light based scanner requires a dedicated NIR enhanced camera and an enclosing box or an IR pass-through filter to block the ambient light, in order to achieve good recognition performances (cf. PROTECTVein results).

Cross-Illumination/cross-spectrum matching At first sight the extracted vein patterns for the different illuminations look identical. However, the experimental results clearly show that cross-illumination matching between reflected light and transillumination achieves a low recognition performance or is not possible at all on the tested data sets. This indicates that the visible vein patterns differ between the illumination conditions. Cross-spectrum matching is feasible between different wavelengths of reflected light, however the performance is lower compared to the single wavelengths. Figure 6 and Figures 7, 8 show some images for VeinPLUS and PROTECTVein, respectively, exhibiting different illumination conditions and the corresponding MC features. One can see that basically the same veins are visible, except for smaller ones, which are more visible for transillumination, but they are not at the exact same positions in the images. For VeinPLUS this might be caused by some hand movement between the acquisitions, which can be ruled out for PROTECTVein. Moreover, the displacement is not the same for all subjects. The left part of Figure 6 corresponds to a subject exhibiting little displacement and the right part to a subject exhibiting a higher displacement, respectively. Figure 9 shows this overlays for the PROTECTVein features in Figure 7 and 8. The overlays reveal that for some subjects there is more displacement between the different illuminations (Figure 9 right) while there is less displacement for others (Figure 9 left).

The different vein displacements are caused by the interaction between the NIR light and the human tissue. 850 nm and 950 nm are subject to different refraction and scattering coefficients of the human tissue [7]. Thus, the refraction angle is different, explaining the displacement between 850 and 950 nm reflected light. Furthermore, the amount of displacement depends on the vertical position of the veins inside the hand due to the light scattering coefficient. The light is scattered and refracted several times while passing through the different layers of tissue inside the hand [7]. Depending on the vertical positions of the veins inside the hand the resulting deviation of the light beams arriving at the image sensor varies. The IDS camera uses a lens with a fixed focal length of 9 mm and an aperture of 2.0. The hand is placed at a distance of about 300 mm from the camera, which is far away from the focal point. Thus, the lens itself introduces distortions increasing with distance from the image centre. Even small deviations/displacements caused by varying light scattering inside the tissue result in bigger ones at the image sensor, finally resulting in significant displacements in the vein images. These displacements cannot be corrected by rotation and translation and resemble the main reason for the low cross-illumination performance.

5. Conclusion

We established two dual illumination dorsal hand-vein data sets, VeinPLUS and PROTECTVein, containing images captured with reflected light and transillumination. PROTECTVein is publicly available, while VeinPLUS is not due to legal issues with the original consent form. Based on these data sets we evaluated several common hand-vein recognition algorithms on each of the sub data sets (reflected light and transillumination), which enabled a direct comparison of reflected light and transillumination in terms of recognition accuracy. Moreover, we matched the images of both illumination scenarios against each other to evaluate the cross-illumination matching performance.

The recognition performance in terms of EER, FMR1000 and ZeroFMR for transillumination outperforms the reflected light one for 2 of the 3 different sensors. For the last one reflected light significantly outperforms transillumination due to the optimal set-up of the camera and illumination. Taking the other advantages of reflected light into account, reflected light is the preferable illumination type for hand-vein recognition.

There is only a small difference between 850 nm and 950 nm wavelength for reflected light, however 950 nm improves the performance when using a NIR enhanced camera. In general, cross-spectrum matching between reflected light 850 nm and 950 nm is feasible but lowers the recognition performance. Cross-illumination matching between transillumination and reflected light is impractical due to vein position displacements caused by light scattering and refraction effects.

We were able to shed some light on the differences between reflected light and transillumination in hand-vein recognition. Our future work will include additional state-of-the-art vein recognition algorithms to further verify our findings. Moreover, we will try to further improve our scanner by doing experiments devoted to the optimal distance between the light source and the hand. Furthermore, we plan to extend our data set (a second session with existing subjects as well as additional subjects) in order to be able to perform gender (e.g. body hair on the dorsal side of the hand), ethnicity (level of skin pigmentation) and age specific experiments (sub-groups). Additionally, we will adopt a model based on the physics of light scattering to restore the vein images and in order to facilitate cross-illumination matching. Finally, we will do biometric fusion experiments to further improve the recognition performance.

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