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Cross Sensor Finger Vein Recognition

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Abstract: If biometric systems are rolled out on a large scale, it will not always be guaranteed that all capturing devices are of exactly the same type. It is therefore important to ensure that the biometric system also works across multiple capturing devices. In finger vein biometry, there is almost no published work in this regard. The biggest problem here is certainly that there are only very few datasets (recorded by different institutions) that usually have no overlap at all with the test persons contained. In a first approach, this article tries to examine how well cross-sensor finger vein recognition works. For the investigation, four publicly available datasets, which were acquired with four different devices in three different scenarios, were evaluated. Using three different finger vein recognition approaches, we will show that the results distinctly deteriorate in cross-sensor recognition scenarios compared to the recognition results using only images from the same device, even more so for image data from contact-less and contact-based capturing devices.

Keywords: Finger Vein Recognition, Cross-Sensor Recognition.

1 Introduction

Vascular biometric systems [Uh19b] have established themselves as serious alternative to systems using traditional biometric traits such as fingerprint, face or iris. Especially systems utilizing the structure of the blood vessels in the palm or fingers, commonly denoted as hand and finger vein biometrics, offer several advantages over traditional modalities. As the vein pattern is located inside the human body and it is only visible in near-infrared (NIR) light, vein images can hardly be acquired without the knowledge of the human subject and no latent variants of it exist [Uh19a].

The performance of finger vein recognition systems mainly depend on the quality and alignment of the acquired sample data. The quality of the vein images is influenced by the physical design and the configuration of the capturing device, whereby the alignment suffers from misplacements of the finger during the acquisition. If the samples are acquired using different devices, further difficulties may arise. E.g. the acquired samples can differ in the size of the finger (scaling), in the finger region that is acquired by the device (whole finger vs parts of it), acquisition quality (resolution, illumination, ...) or the degrees of freedom in positioning the fingers on the device. Some devices provide different finger placement units to prevent e.g. misplacements of the finger right from the beginning, while others allow an almost unconstrained positioning of the fingers (contactless scenario).

This work aims to find out how well finger vein recognition systems perform when the subjects have been acquired using different capturing devices (sensors). The analysis includes four different datasets for which the finger vein samples have been acquired using

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four different sensors. The evaluation utilizes a widely used correlation-based method and state-of-the-art key-point and CNN-based recognition systems.

So far, little work has been done on cross-sensor recognition for finger veins. In [KPU18a], the authors compared images acquired with two different versions of the same capturing device: the only difference was the illumination module. Both sensors use trans-illumination but different light sources (NIR LEDs vs NIR laser diodes). The results indicate that cross-sensor recognition is possible, but results in a noticeable performance degradation. Depending on the used recognition scheme, the relative error increases are between 160 and 2340%. The two datasets used in [KPU18a] are also evaluated in this work. In [KU18] the authors conducted a similar experiment utilizing dorsal hand veins. Again, they compare different illumination scenarios: trans-illumination vs reflected light with two different wavelengths. While for cross-spectrum comparisons (reflected light with different wavelengths), the drop in performance was similar to the finger vein experiments in [KPU18a], the drop for the cross-illumination experiments (trans-illumination vs reflected light) was much higher. To the best of our knowledge, there is no further work on this topic.

2 Datasets and Capturing Devices

2.1 PLUSVein-FV3 Finger Vein Data Set

The *PLUSVein-FV3 Finger Vein Data Set* (PLUS-FV3, [KPU18b]) comprises dorsal as well as palmar finger-vein images captured from the same subjects from six fingers (left and right index, middle and ring finger). The dataset provides high resolution palmar and dorsal finger-vein images of 360 individual fingers from 60 subjects. For this dataset (as well as all other datasets evaluated in this article) 5 samples per finger have been acquired. It contains four subsets: dorsal and palmar images captured with the NIR LED and NIR laser module based version of the *PLUS OpenVein Finger Vein Scanner* [KPU19]. The finger-vein scanner was built in a way that requires the subject to place the whole hand in a defined position flat on the placement unit. Therefore, the data is expected to contain little to no misplacements. As camera the IDS Imaging UI-ML3240-NIR is employed. In this work, the two palmar subsets (PLUS-FV3-Laser and PLUS-FV3-LED) are used.

2.2 PLUSVein-Finger Rotation Data Set

The *PLUSVein-Finger Rotation Data Set* (PLUSVein-FR, [PKU18]) contains a total of 252 unique fingers from 63 different subjects, 4 fingers per subject (left and right index and middle finger). The fingers were acquired as videos where one frame corresponds to a rotation of 1°. This results in 361 images per acquisition. As light source the same NIR laser modules as for the PLUS-FV3-Laser were used. Same as for PLUS-FV3-Laser and PLUS-FV3-LED, the IDS Imaging UI-ML3240-NIR camera is employed (same model, different camera) . Contrary to the *PLUS OpenVein Finger Vein Scanner*, for this finger-vein scanner the finger is placed relatively unconstraint with support structures just for the tip and tail of the finger. Of course, this results in a higher degree of freedom of the acquired images. In this work, only images from the palmar view (0°) are used. 60 of the 63 subjects are also part of the PLUS-FV3 database.

2.3 PLUSVein-Contactless Finger and Hand Vein Data Set

The *PLUSVein-Contactless Finger and Hand Vein Data Set* (PLUSVein-CL, [KPU19]) consists of 3 subsets: a palmar finger vein one, acquired using light transmission illumination and two hand vein ones. Currently, the finger vein database contains 42 subjects, with 6 fingers (left and right index, middle and ring finger) and two hands (left and right hand) per subject. As the name of the dataset already suggests, the data was acquired in a contactless scenario. Therefore, this dataset has the highest degree of freedom from all evaluated datasets. In this work only the finger vein subset is used. As camera the IDS Imaging UI-1240ML-NIR is employed. 18 of the 42 subjects are also part of the PLUS-FV3 database.

2.4 PROTECT MultiModal Data Set

The *PROTECT MultiModal Data Set* (PMMDB, [Ga20]) includes different biometric modalities, namely iris, face (visual light, NIR, 3D and thermal), periocular, anthropometrics and hand- and finger veins of 69 different subjects. It was acquired in two data acquisition events with one year between the two events. In the second acquisition event, the finger vein data has been acquired with the same capturing devices as used for PLUS-FV3 (LED and Laser version) and PLUSVein-FR. The three subsets are denoted corresponding to their counterparts: PMMDB-FV3-Laser, PMMDB-FV3-LED and PMMDB-FR.

Figure 1 shows sample images of data acquired for all datasets/capturing devices.

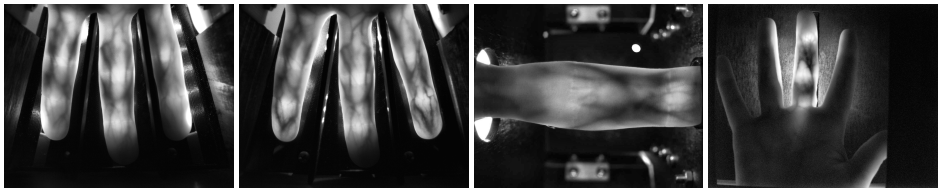

Fig. 1: Acquired finger vein images for (from left to right) PLUS-FV3-Laser/PMMDB-FV3-Laser, PLUS-FV3-LED/PMMDB-FV3-LED, PLUSVein-FR/PMMDB-FR and PLUSVein-CL.

2.5 Training and Evaluation Data

In order to ensure a 100% separation of training and evaluation data, we used the data from the PMMDB for training and the one from PLUSVein-FR, and PLUS-FV3 for evaluation. As there is no corresponding dataset for the PLUSVein-CL, the data had to be divided into training and evaluation data. The separation has been done based on subject (all images of a subject from PLUSVein-CL are either part of the training or evaluation set). Persons who also took part in the data acquisition for PLUSVein-FR and PLUS-FV3 are in the evaluation set (18 subjects), all others (24 subjects) in the training set.

For training only data of the indoor session of the 2nd acquisition event (due to quality reasons) of PMMDB-FR and PMMDB-FV3 (LED and Laser) was used. In this session 6 fingers from 18 subjects have been acquired. As mentioned above, images of 24 subjects of the PLUSVein-CL are also part of the training data. While for PMMDB-FR and

PMMDB-FV3 the exact same subjects are acquired, for PLUSVein-CL there is only an overlap of 2 subjects to the other datasets. This puts the PLUSVein-CL at a disadvantage when executing cross-dataset experiments. Although only index and middle fingers were acquired for PMMDB-FR, the acquired ring finger images of the other datasets have also been used for training. The employed methods are either trained using only training data from one of the four datasets or the combined training data from all four dataset (Combined DB_{TR}).

For evaluation we only use data of fingers, that have been acquired for all four datasets (index and middle finger of both hands from PLUS-FV3-Laser (Laser), PLUS-FV3-LED (LED), PLUSVein-FR (FR) and PLUSVein-CL (CL)). This results in 72 unique fingers or 360 images (5 samples per finger) from 18 different subjects. Evaluation is applied on the individual datasets as well as on the combined evaluation of all images from all four datasets. Combined DB_{EV} therefore contains 20 samples per finger or 1440 images in total.

3 Experiments

In finger vein recognition, the majority of algorithms can be grouped in three different categories: (1) Correlation based schemes, where the vein pattern is extracted into binary templates and compared to each other, (2) key-point based methods and (3) CNN-based methods. In this work the experiments were carried out using one representative of each of these three categories: *Maximum curvature* (MC, [MNM07] - correlation based), *deformable finger vein recognition* (DFVR, [Ch17] - key-point based) and *SqueezeNet* architecture using the *triplet loss function* together with *hard triplet online selection* (Triplet-SqNet, [WPU20] - CNN-based method). The experiments have been carried out using existing publicly available implementations of the evaluated recognition schemes: MC [KU19], DFVR [PU21] and Triplet-SqNet [WPU20]. For MC we used *circular Gabor filter* (CGF) [ZY09] and simple *CLAHE* (local histogram equalization) [Zu94] for contrast enhancement, for DFVR only *CLAHE*. For Triplet-SqNet the images are only normalized to zero mean and standard variance. The experiments are carried out following the protocol of the FVC2004 [Ma04].

3.1 Region of Interest Extraction

For the region of interest (ROI) extraction, the finger region has been segmented using the CNNs models provided by [Pr22]. Next, the fingers are normalized (re-sized) so that the average finger thickness is the same (224 pixel) for all images. The actual ROI of size 480x192 is cut out horizontally centered and 168 pixel (¾ of the normalized finger width) from the finger tip. In order to avoid any influence of the ROI extraction on the experimental results, we visually compared the outputs of the three segmentation CNNs from [Pr22] and manually selected the best output. If none of the outputs were close to a perfect segmentation, we manually segmented the corresponding images.

3.2 Parameter Optimization and Experimental Setup

Parameters are optimized using the training data. For MC we optimized sigma from feature extraction, horizontal and vertical shift as well as the rotation for comparison. For DFVR, the parameter r (radius of the local neighborhood to create a vein map) was set manually (based on the visual impression of the authors) to the same value 12 for all training datasets. Afterwards, SIFT and PCA were calculated exactly as described in the original DFVR paper for each dataset. Triplet-SqNet is trained using the same parameters as in [WPU20] (same training parameters (nr. of epochs, learning rates,...), 256-dimesional output vector, CNN is pre-trained on the ImageNet database and fine-tuned on the training data). Distances between CNN outputs of evaluation images are measured using the Euclidean distance d and similarity scores are computed by inverting the distances ($1/d$).

The first series of experiments is applied using different training and evaluation datasets including Combined DB. In a second series of experiments we aim to find out if the methods are able to recognize vein images of one specific dataset based on images of another one. This cross-data-set experiments are applied with all combinations of two datasets each. This means that for each pairing of two datasets, only similarity scores between images of different datasets are used for the EER computation. Because of the high number of experiments and to simplify the comparison of the results, we only report the EER without FNMR and FMR.

3.3 Evaluation and Discussion

In Table 1 we present the results using each of the training datasets for parameter training (including Combined DB) and each of the evaluation datasets for evaluation. The most meaningful outcomes with respect to cross-sensor finger vein recognition are those using the Combined DB evaluation dataset, since only for the experiments using this evaluation dataset similarity scores between images of different datasets (and sensors) are used for the EER computation. We can observe that MC and DFVR always achieve similar results between about 21 and 24% for evaluations on Combined DB_{EV}. For the CNN, the results vary greatly depending on the used training data and the best result (16.5%) is achieved for training on the combined training data. The two methods MC and DFVR achieve clearly better results for evaluations on single evaluation datasets than CNN if only a single training dataset is used for training. In case of using the combined training data from all training datasets, the CNN results are overall similar to the results of the two hand-crafted methods.

Summarized, the results drop by huge amounts when images of different datasets are compared (Combined DB_{EV}).

What we cannot find out from the experimental results shown in Table 1 is if the recognition between images of different datasets does work poor in general or if it only does not work between images of specific datasets while performing well on others. This open question can be answered by our second series of experiments. In Table 2 we present the cross-dataset results between the images of two evaluations datasets each. For the calculation of the EER, only similarity scores between images of the two different evaluation

$\downarrow$ train \ eval $\rightarrow$	Laser_{EV}			LED_{EV}			FR_{EV}			CL_{EV}			Combined DB_{EV}		
	M	D	C	M	D	C	M	D	C	M	D	C	M	D	C
Laser_{TR}	0.3	0.2	3.5	0.1	0.7	3.5	2.4	0.9	7.9	1.3	2.6	7.4	20.5	23.6	34.2
LED_{TR}	1.5	0.3	1.9	0.4	0.7	2.0	2.8	0.9	8.8	4.9	2.8	7.0	24.4	23.6	29.9
FR_{TR}	0.3	0.2	1.0	0.2	0.7	1.4	1.8	0.9	3.3	1.3	2.6	5.4	21.7	23.7	22.2
CL_{TR}	0.0	0.2	1.0	0.1	0.7	2.2	2.5	0.9	7.9	1.1	2.5	1.2	21.4	23.3	30.0
Combined DB_{TR}	0.4	0.3	0.8	0.0	0.7	0.2	2.2	1.1	1.7	1.5	2.8	0.9	20.7	24.0	16.5

Tab. 1: Results (EER in %) of the three recognition schemes using different datasets for training (TR) and evaluation (EV). The first result in each row of a column is for MC (M), the second for DFVR (D) and the third for CNN (C).

datasets are taken under account, but not similarity scores between images of the same dataset (except if the two evaluation datasets are one and the same). For this series of experiments, the three recognition schemes were optimized/trained all with the combined training data from all datasets.

When looking at the results, we can observe that the results for cross-dataset evaluation between the Laser and LED evaluation datasets are only slightly worse compared to the results on just the Laser or LED datasets for MC and DFVR and only moderately worse for CNN. Similar results have already been reported in [KPU18a] and [KU18]. For the cross-dataset experiments between one of the PLUS-FV3 datasets (Led or Laser) and the FR dataset, the results are distinctly worse with EERs of about 10% for DFVR and CNN and 16% for MC. Cross-dataset evaluations between the CL dataset (contactless acquisition) and any of the other three datasets achieve the clearly worst results with EERs of about 25% for CNN and EERs of over % for MC and DFVR.

	Laser_{EV}			LED_{EV}			FR_{EV}			CL_{EV}		
	M	D	C	M	D	C	M	D	C	M	D	C
Laser_{EV}	0.4	1.4	0.8	0.4	2.0	3.8	17.2	9.4	10.9	31.0	31.7	25.3
LED_{EV}	0.5	2.0	3.8	0.0	1.4	0.2	15.1	8.8	10.0	32.1	31.7	23.8
FR_{EV}	19.4	9.4	10.9	17.2	8.8	10.0	2.2	1.8	1.7	34.5	32.5	24.9
CL_{EV}	31.4	31.7	25.3	32.0	31.7	23.8	32.4	32.5	24.9	1.5	3.1	0.9

Tab. 2: Cross-dataset results (EER in %) of the three recognition schemes for each pairing of the four evaluation datasets. The first result in each row of a column is for MC (M), the second for DFVR (D) and the third for CNN (C). The recognition schemes were optimized/trained using the training data from Combined DB_{TR}.

4 Conclusion

In this work we showed that finger vein recognition systems have huge problems when the image data is acquired from different capturing devices. Experiments were carried out using two classical finger vein recognition methods (MC and DFVR) and a CNN-based approach (Triplet-SqNet). When the input samples have been acquiered in a similar set-up (the capturing devices differed only in the light source, Laser vs LED), then the deterioration of the recognition results are rather small compared to having images acquired

with the exact same device. However, if the acquisition devices are more different, but still act contact-based (PLUS-FV3 vs PLUSVein-FR), then the performance degradation is noticeable higher. Instead of EERs <1.5%, only EERs between 10 and 17% are achieved. If contact-based data (PLUS-FV3 andPLUSVein-FR) is compared to data acquired in an contact-less scenario (PLUSVein-CL), the recognition performance further drops to EERs between 25% (CNN) and over 30% (MC and DFVR). That means a reliable recognition task is not possible anymore.

For the dataset Combined DB_{EV}, that includes evaluation images from all four datasets, EERs were achieved between 16.5% and 34.2%. This is distinctly worse than the results using only image data from one dataset. In this case, the results are mostly below 2% for the 2 hand-crafted approaches MC and DFVR (even if the methods are trained using image data from other datasets), and below 9% for Triplet-SqNet. In case of the CNN-based approach, we could observe that the number of training images has a huge impact on the results. Using only training data from one dataset, the CNN clearly performed worse than the two hand-crafted approaches for the experiments with evaluation data from only one dataset. When using training data from all 4 datasets (Combined DB_{TR}), the CNN results are comparable to the ones of the hand crafted approaches. For the experiments using evaluation data from all devices for training and evaluation, the CNN even outperformed the hand crafted approaches (EER=16.5%).

In summary, cross-sensor finger vein recognition seems to be a challenging task. Although nearly perfect ROIs (aligned horizontally and vertically and normalized by average finger width) were available, the results for state-of-the-art recognition schemes (correlation-, key-point- and CNN-based) are disappointingly poor. This means that further improvements such as rotation correction (performs slightly better, results can be integrated into a full research paper) have to be added to the recognition tool-chain.

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