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# Pre-Processing Cascades and Fusion in Finger Vein Recognition

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**Abstract**—Preprocessing and fusion techniques for finger vein recognition are investigated. An experimental study involving a set of preprocessing approaches shows the importance of selecting the appropriate single technique and the usefulness of cascading several different preprocessing methods for subsequent feature extraction of various types. Score level fusion is able to significantly improve recognition results, in particular when combining features describing complementary finger image properties.

## I. INTRODUCTION

Authentication based on finger veins uses the pattern of the blood vessels inside the fingers of a human. Compared to fingerprint authentication using finger veins has several advantages. The veins are underneath the skin so the vein pattern is resistant to forgery as the veins are only visible in infrared light. Also liveness detection is easily possible. Moreover the vein patterns are neither sensitive to abrasion nor to finger surface conditions, like dryness, dirt, cuts, etc. But there are also some disadvantages. First of all, so far it is not completely clear if vein patterns exhibit sufficiently distinctive features to reliably perform biometric identification in large user groups. With the currently available data sets (see Table I, the public ones available on-line: ChonbukU<sup>1</sup>, PekingU<sup>2</sup>, PolyU<sup>3</sup>, TwenteU<sup>4</sup>) this issue cannot be clearly answered at present state due to their partially limited size.

TABLE I. FINGER VEIN DATASETS.

Acronym	Availability	# Images	# Subjects / # Fingers	Ref.
ChonbukU	public	6000	100 / 600	[1]
ChongqingU	private	4260	71 / 426	[2]
DonggukU	private	4800	60 / 480	[3]
HarbinU	private	100	10 / 10	[4]
HITACHI	private	678	339 / 339	[5]
NTUST	private	680	85 / 170	[2]
PekingU	public	50700	5208 / n.a.	[6]
PolyU	public	6264	156 / 312	[7]
TwenteU	public	1440	60 / 360	[8]

Another major disadvantage is that the capturing devices, due to the required transillumination principle, are rather big compared to e.g. fingerprint sensors. Furthermore, the vein structure is influenced by temperature, physical activity and certain injuries and diseases. While the impact of these effects on vein recognition performance has not been investigated

in detail so far, consequently it is clear that suitable feature extraction methods should be independent of the vein width to compensate for corresponding variations.

The first issue tackled in this paper is the low contrast and the low overall quality of finger vein images in general. The nature of these images (see e.g. an example of a good and a poor quality image pair in Fig. 1) requires to apply successful preprocessing in order to achieve decent recognition performance, no matter which feature extraction strategy is applied. However, it is difficult to compare the various preprocessing strategies since these are dispersed across literature and are often combined with a single feature extraction technique only (and applied to different, sometimes non-public, datasets). In this paper, we compare a set of preprocessing techniques in a common framework applied with various feature extraction techniques to identify good combinations. We also apply more than a single preprocessing technique, but contrasting to [9] we do not fuse the results before feature extraction but apply different techniques in a cascaded manner.

In order to improve finger vein recognition results, several fusion techniques have been investigated in literature. Fusion of several fingers' results is an obvious possibility [10], [2], however, sensing is more expensive in this approach of course. Using multiple features extracted from a single image in a score level fusion (by analogy to fusion of e.g. palm vein data [11]) has resulted in first promising results: Fusion of vein pattern structure, LBP, and super-pixel features [12] as well as fusion of vein-shape, vein orientation, and SIFT features [2] were able to improve the usage of single features. Especially in the latter paper in case of using high accuracy features improvements have been found to be moderate only. In this work we show that features representing orthogonal finger-vein image properties lead to significantly improved accuracy in a score level fusion scheme, even in case the single techniques involved exhibit partially poor recognition accuracy.

The rest of the paper is organised as follows: Section 2 describes techniques for finger vein recognition (i.e. preprocessing and feature extraction approaches) while Section 3 describes the experimental setting and provides results with respect to the selection of preprocessing strategies and score level fusion. Section 4 concludes this work and gives an outline of future research.

<sup>1</sup><http://multilab.chonbuk.ac.kr/resources>

<sup>2</sup><http://rate.pku.edu.cn>

<sup>3</sup><http://www4.comp.polyu.edu.hk/~csajaykr/fvdatabase.htm>

<sup>4</sup><http://www.sas.el.utwente.nl/home/datasets>



**Maximum Curvature** (MC [17]) emphasises the center-lines of the veins and is therefore insensitive to changes in the width of the veins. At first the center position of veins is extracted. For this purpose, the local maximum curvature in cross-sectional profiles in four directions, horizontal, vertical and the two oblique directions, based on the first and second derivatives, is determined. Then each profile is classified as being concave or convex (curvature positive or negative) where local maxima in concave profiles indicate the center positions of the veins. Each center position is then assigned a score, according to the width and curvature of the region.

Subsequently, the center positions of the veins are connected. Due to noise or other distortions some pixels may not have been classified correctly at the first step, so a filtering operation is applied in all four directions taking adjacent context pixels into account. The last step is the binarisation of the vein pattern using the median of the locus space as a threshold.

The **Wide Line Detector** (WLD [6]) works similar to adaptive thresholding (using isotropic nonlinear filtering), i.e. thresholding inside a local neighbourhood region. The difference of each pixel inside a circular neighbourhood to the central pixel is determined. Subsequently, the number of pixels inside this neighbourhood which have a difference smaller than a set threshold are determined. This number is again thresholded to get the final binary vein image. See Figs. 2.d and 2.j for an example binarisation of this type.

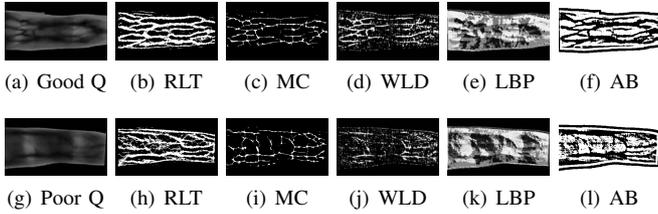


Fig. 2. Feature extraction examples.

Given the title of the paper [7], it is somewhat surprising to find highly competitive finger vein feature extraction techniques: **Gabor Filtering** (EGM) is suggested by taking the maximal response in each pixel by using a convolution of self similar 2D even Gabor filters for different orientations with a zero-mean version of the image. Subsequently, a morphological top-hat operation is performed (i.e. subtracting the Gabor response image from a version that has undergone morphological opening) to generate the binary result. **Matched Filters** (MF [7]) are used to match cross section profiles of finger veins employing a group of 1-D Gaussian functions. Similar to the Gabor case before, the employed Gaussian functions are rotated in different orientations and only the maximum response is utilised. Binarisation is conducted in the same manner.

To assess the advanced binarisation techniques which try to model vein shape in their binarisation strategy as described so far, we have additionally used basic **Adaptive Binarisation** (AB [18]) to see the (eventual) effect of the more advanced schemes. See Figs. 2.f and 2.l for an example binarisation of this type and please note, that contrasting to the other binarisation techniques discussed (i) veins appear black and (ii) also the outline of the finger causes a strong black

curve indicating its shape. Thus, in addition to show the vein structure we additionally get finger shape information for free.

As the last binarisation-type feature extraction scheme, we consider a **Local Binary Patterns** (LBP) feature extraction scheme [3]. LBP compare the grey level of a center pixel to its neighbouring pixels. The original LBP is a 3x3 non-parametric operator. It can also be defined as an ordered set of binary values determined by comparing the gray values of a center pixel to its 8 neighbouring pixels. Each image gray scale value is replaced by the corresponding binary code resulting from the binary pattern of the neighbourhood (which results in binary images of 8-fold size of the binarisation results discussed so far).

Lee et al. [3] used an LBP approach for finger vein matching, preceded by a minutia-based alignment step and a Hamming distance matching. We followed their approach for feature extraction but moved the alignment into the matching stage and used a multi-scale LBP version instead (due to better results). See Figs. 2.e and 2.k for an example binarisation of this type.

For matching a pair of binarized image features we adopt the approach in [5] and [17]. As the input images are not registered to each other and only coarsely aligned, we simply calculate the correlation between the input image and the reference one while shifting the reference image in x- and y-direction. The maximum value of the correlation is normalised and used as matching score.

While binarisation techniques (with the exception of LBP) compute a single bit of information for each pixel in the original image, the importance of neighbourhood information is already accounted for in how these single bits are computed in most techniques as discussed before as well as in the super-pixel approach of Liu et al. [12]. As already discussed, an entirely different approach is to use vein minutiae representing the most discriminative local information contained in the images. A different approach combining both ideas, i.e. highlighting the most discriminative points as well as the importance of neighbourhood and context information, is the employment of key-points and their descriptors. In this work we consider SIFT [19] and SURF [20]. See Figs. 3.a and 3.b for a visualisation of extracted keypoints.

SIFT keypoints have been considered in palm vein image recognition [21] with moderate success only. Peng et al. [4] propose an approach for finger vein images based on CLAHE and an orientation-selective Gabor filtering (responses of two two Gabor filters with orientations  $\frac{2\pi}{8}$  and  $\frac{7\pi}{8}$  are fused) with subsequent matching based on SIFT feature extraction on the filtered images. Qin et al. [2] use SIFT to identify distinctive corresponding sub-regions in finger vein images and apply matching to those regions only.

As can be seen from the SURF feature extraction example (see Fig. 3.b), there are many strong keypoints along the finger boundaries. As descriptors of such keypoint contain irrelevant background information, including them can lead to false or ambiguous matches. Thus we implemented a filtering step within a window along the finger boundaries (whose width can be defined). All keypoints inside the window are discarded (keypoint filtering, see Fig. 3.c). In addition, a minimum number of keypoints can be defined. If too few keypoints are

found, feature extraction is re-run with adapted parameters to extract more keypoints until at least the minimum number of keypoints are found or the parameters cannot be changed any more.

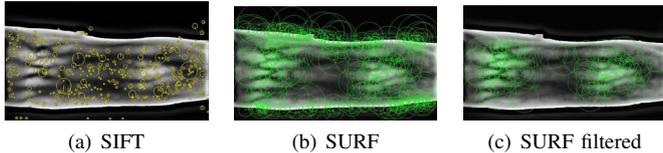


Fig. 3. SIFT & SURF feature extraction.

SIFT and SURF matching is done using the keypoint descriptors – the keypoint with the smallest distance to the reference keypoint is the matched one if the distance is below a threshold, otherwise there is no match. To resolve the problem with ambiguous matches (i.e. one keypoint may have small distances to more than one other point) a ratio threshold is used: A match is only valid if the distance of the best point match is at least  $k$  (threshold) times smaller than to all other points.

After matching we get a set of matched keypoints with associated distances. The simplest way (and also best one, at least for SURF) to get a final matching score is to use the number of matched keypoints only. A slightly better way (for SIFT) is to use the ratio of matched keypoints to the maximum possible number of matches (minimum number of keypoints of the two images) – “ratio score calculation”. All techniques involving also distances of matched keypoints performed worse and thus have not been considered further.

Comparing the accuracy of the different techniques as given in literature, Table II shows that reported EERs (1) highly depend on the dataset (2) are not even consistent among different implementations when applied to the same dataset (3) tend to be lower in the original publications as compared to re-implementations. Thus, at current stage, it is almost impossible to make recommendations concerning the “best” technique based on the data available.

### III. EXPERIMENTS

#### A. Experimental Settings

For our evaluation we use the TwenteU dataset. This dataset (see Table I) consists of a total of 1440 images, taken from 60 persons, 6 fingers per person (index, ring and middle finger of each hand) and 4 images of each finger. The images were captured in 2 sessions with a time-lag of 15 days between the sessions using a custom designed transillumination device. Each finger was captured twice during one session. 73% of the subjects were male and 82% were right handed. The images have a resolution of 672 x 380 pixels, a density of 126 pixels/cm and are stored in 8 bit grey scale PNG format. The width of the visible blood vessels is 4 - 20 pixels.

RLT, MC, WLD feature extraction and matching are used as provided in a MATLAB implementation by B.T. Ton<sup>5</sup>. SIFT and SURF software is used as provided by OpenCV, custom

implementations are used for the preprocessing techniques, LBP, SIFT and SURF keypoint filtering, and AB. Images have been downsampled by a factor of 2 in both dimensions as the MATLAB software is customised to the expected vein width of this image scale.

In order to be able to compare our results to those in [8] (compare Table II [8] to Table V) we applied the same EER determination procedure: Only one finger of each of the first 35 subjects is used as training set for parameter tuning. The actual EER determination with the rest of the dataset consists of 1950 genuine matches and 842400 impostor matches compared into FAR and FRR, respectively.

Considering score level fusion as used in this work, the simple MinMax normalisation turned out to be the best. We tested different score combinations, from pairs of 2 scores to tuples of all available scores, each one with different fusion schemes (including weighted sum, weighted product, weighted mean/median and weighted minimum/maximum) and systematically assessed all variants with different weight combinations on the parameter optimisation test set.

#### B. Experimental Results

The first results (Tables III and IV) are devoted to preprocessing strategies. For these results, computational load has been reduced due to costly exhaustive configuration testing – N preprocessing stages can be combined into N! different combination configurations – by restricting the impostor matches to comparing each image with the corresponding finger/image of each other person only but used the entire dataset instead of 90%. Thus, these results cannot be compared directly to the results in Table V.

The results in Tables III and IV are cumulative, i.e. for a given line all the above lines were also applied to achieve the final result. An important thing to note is that parameters are not independent from each other, which means if e.g. the feature extraction parameters are changed also the matching parameters have to be re-adjusted.

TABLE III. PREPROCESSING IMPACT ON EER (%) OF SIFT.

Without any preprocessing	18.82
Filtering of keypoints along the finger edges	10.66
Feature Extraction parameter adjustments	9.65
Matching parameter adjustments	9.00
CLAHE	8.26
Resizing (0.5)	6.44
HFE Filtering	2.74
Gabor Filter	2.59
Ratio Score Calculation	2.04

As it can be seen easily in Table III for SIFT-based recognition, keypoint filtering and HFE filtering exhibit the most significant positive impact on the EER. Interestingly, we are able to improve EER in several successive stages from applying SIFT without any preprocessing at EER of 18.82% to the highly tuned variant at EER of 2.04% involving several preprocessing and matching optimisations and variants.

Table IV compares preprocessing cascades for the other recognition approaches considered. While up to LeeRegion detection all feature extraction techniques are able to take advantage from preprocessing, the optimal EER is achieved at

<sup>5</sup>Publicly available on MATLAB Central: <http://www.mathworks.nl/matlabcentral/fileexchange/authors/57311>

TABLE IV. IMPACT OF PREPROCESSING ON EER (%).

Preproc.	MC	WLD	RLT	LBP	AB	SURF
none	6.443	32.19	22.63	34.1	7.223	13.81
Resize (0.5)	2.041	10.18	4.03	32.67	4.872	9.843
LeeRegion	1.989	9.96	4.11	31.45	4.816	9.843
Normalisation	0.7831	4.777	2.04	29.67	3.606	11.45
CLAHE	0.6011	<b>2.687</b>	<b>1.856</b>	11.55	3.376	11.88
Circ. Gabor Filter	<b>0.4692</b>	3.116	1.999	9.895	<b>3.335</b>	11.58
HFE Filter	0.7399	3.804	5.785	10.75	3.807	<b>4.184</b>
Denosing	0.9255	2.918	5.662	<b>6.043</b>	3.508	4.275

different stages of the cascade, SURF results degenerate until HFE application where the minimal EER value is reached at 4.18%. RLT and WLD reach their optimum at EER of 2.69% and 1.86% when using CLAHE, respectively. The additional circular Gabor filter application delivers the best results for MC and AB at 0.49% and 3.34%, respectively. Finally, for LBP, the best result (EER 6.04%) is achieved when applying a final denosing stage after having applied the circular Gabor filter and CLAHE. Summarising we may state that there is no unique best preprocessing cascade to be identified, but in any case it gets clear that some feature extraction techniques benefit from a cascaded preprocessing application while others suffice with a restricted set only.

Table V lists the results of the overall best preprocessing cascades / feature extraction combinations achieved over the entire evaluation dataset. We achieve the top EER at 0.42% for MC and the worst one for LBP at 5.03%. It is interesting to see that the generic SIFT approach outperforms the highly specialised WLD and that even the simple AB technique is not much worse.

TABLE V. COMPARISON OF EERS (%) OF RECOGNITION METHODS CONSIDERED.

	MC	WLD	RLT	SIFT	SURF	LBP	AB
EER	<b>0.42%</b>	2.87%	1.64%	1.96%	4.34%	<b>5.03%</b>	3.23%

Figure 4.a displays ROCs for all combinations in Table V (WLD: yellow, LBP: magenta, MC: cyan, RLT: red, SIFT: green, SURF: blue, and AB: black). While in terms of EER, AB is superior to SURF, for lower FAR values SURF gets superior quickly. The remaining schemes maintain the EER ranking almost consistently. Figure 4.b shows the ROC of the best fusion technique which is obtained using weighted sum fusion (weights: 1.2, 3.2, 1.1) of LBP, MC, and AB at an EER of 0.25%. Also the ROCs of the three single techniques are included for comparison (Fusion: red, LBP: green, MC: blue, AB: black).

It is interesting to observe that the best fusion result is not obtained by combining the three best performing techniques but in contrast, by combining the best performing single technique with the two worst ones. Obviously, it is not the single performance that determines the final fusion result. While MC captures the structure of the veins most efficiently, AB contributes finger shape and LBP adds general texture information also between veins (mainly local information around the pixels and not lines are extracted). Thus, those three technique can really be said to contribute quite orthogonal properties of the finger region. Another good result was achieved using a combination of MC, LBP and SIFT with weighted product

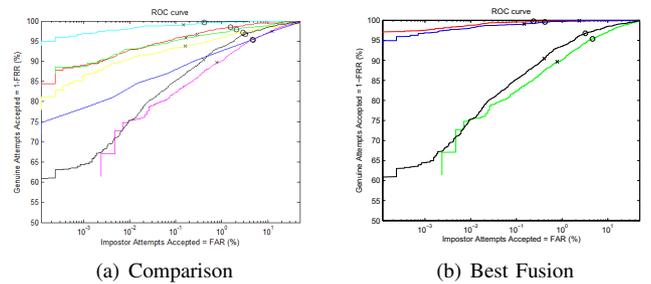


Fig. 4. ROC results

fusion (weights 0.7, 2.8, 1.4) resulting in an EER of 0.27%. Here similar considerations concerning opposing properties do apply.

#### IV. CONCLUSION

Preprocessing has a major impact on the recognition performance of different feature extraction techniques. There is neither a single preprocessing approach nor a single preprocessing cascade that is the optimal technique for all subsequent feature extraction techniques. In contrary, preprocessing needs to be carefully optimised for each single feature extraction method. We have found that cascading different preprocessing techniques significantly improves recognition performance as compared to applying a single approach in many cases.

Score level fusion has turned out to improve recognition performance considerably, especially when combining features which represent complementary properties of the images' finger regions. In these combinations, not only vessel structure but also finger shape and non-vessel texture is represented, leading to EERs superior to the best EERs of single techniques by almost 100% .

With respect to fusion, we aim to further investigate the inclusion of Gabor and Matched Filter feature extraction as well as vein-minutiae informations to further improve results.

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