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LETTER

Hand-Dorsa Vein Recognition Based on Scale and Contrast Invariant Feature Matching

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SUMMARY The ignored side effect reflecting in the introduction of mismatching brought by contrast enhancement in representative SIFT based vein recognition model is investigated. To take advantage of contrast enhancement in increasing keypoints generation, hierarchical keypoints selection and mismatching removal strategy is designed to obtain state-of-the-art recognition result.
key words: *vein recognition, contrast enhancement, feature selection, mismatching removal*

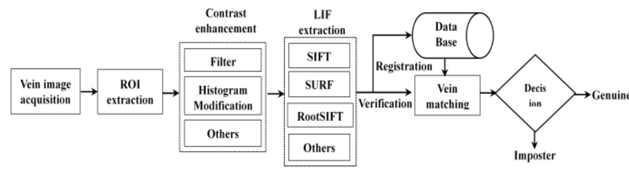

Fig. 1 General framework of LIF based vein recognition system

1. Introduction

Vein recognition has emerged as a new biometric trait for accurate and fast people identification recently, and has received growing attention as a result of live-body and anti-interference identification, simple-acceptability and anti-counterfeit pattern [1]. A general framework for vein recognition usually refers to contrast enhancement (CE), feature extraction and matching. Among numerous researches for reliable vein recognition, nearly half of them focus on robust feature extraction model design from different perspective. For example, the famous curvature information and Gabor filter design to obtain the distinguished geometry-based feature; the classical LBP and image invariant moment method to represent the statistical feature; the SIFT or SURF for local invariant feature extraction.

To construct a less-constrained vein recognition system which renders no restriction on hand gesture and location, distance of hand from capturing device, only the local invariant feature based system is effective. However, if the local invariant features are directly extracted from the images, it is difficult to obtain sufficient keypoints because hand vein imaging under near-infrared (NIR) illumination usually appear dark and low contrast [1]. To address this problem, nearly all SIFT/SURF based vein recognition system (as illustrated in Fig. 1) incorporates CE as the necessary pre-processing step with state-of-the-art recognition results reported [4]. However, conclusions in [2], which bring evidence that the number of SIFT keypoints resulted by gradient based detectors increases greatly with CE, while on the other hand the matching result of extracted invariant descriptors is negatively influenced in terms of Precision Recall (PR) and Equal Error Rate (EER), motivate us to rethink and investigate the overall effect of CE on SIFT based vein recognition system, and also design the scale and contrast invariant feature matching (SCIFM) strategy to construct more robust vein recognition system. Comprehensive experiments verify that the negative influence of CE on SIFT in [2] is the same with SIFT based vein recognition system, and state-of-the-art recognition result fully demonstrates the effectiveness of the proposed SCIFM strategy in mismatching removal.

2. Analysis on the Effect of CE on SIFT

In this part, the contrary effect of contrast enhancement on SIFT feature detection and matching reflecting in increasing keypoints generation and mismatching simultaneously is experimented and discussed.

To sufficiently investigate the specific influence of different CE on the performance of SIFT based vein recognition system which reflects in keypoints number and PR/EER value change respectively, nearly all CE methods adopted in the published SIFT based vein recognition system are re-experimented, followed by keypoints detection and matching to evaluate the specific influence. The involved CE methods cover HE (histogram equalization), IN (intensity normalization), IHE (illumination estimation subtract and HE), DHE (DoG filter and HE), HF (holomorphic filter), GC (gamma correction), RASF (Retinex and adaptive smoothing filter), CLAHE (contrast limited adaptive histogram equalization), and related AHE (adaptive histogram equalization), CLHE (contrast limited histogram equalization), HHE (high frequency filtering and HE), INE (image negative enhancement), GLS (gray level slicing), CS (contrast stretching), LS (laplacian sharpening), UM (unsharp mask-

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Table 1 Statistical keypoints number change brought by different CE methods. Avg and Time represents average keypoints number and magnification of the overall database before and after CE.

Model		LNFE				
	Original	IN	GLS	GC08	CS	LS
Avg	12	17	65	12	16	15
Times	1	1.4	5.4	1	1.3	1.3
Model		UM	HF	HBF	INE	
		91	11	17	11	
		7.6	0.9	1.4	0.9	
Model		HEs				
	Original	HE	AHE	CLAHE	CLHE	
Avg	12	34	337	55	32	
Times	1	2.8	28.1	4.6	2.7	
Model		HEM				
	Original	IHE	DHE	HEHBF	RASF	HHE
Avg	12	129	479	70	87	149
Times	1	10.8	39.9	5.8	7.3	12.4

ing), HBF (high boost filtering), HEHBF (HE and HBF). To the best of our knowledge, the entire listed CEs have been reported to boost the final SIFT based vein recognition system performance in terms of EER. Carried with the confidence from the published papers that performance will be improved, and with the evidence judging from the conclusion illustrated in [2] that performance will be kept unchanged or declined, it is necessary to conduct comprehensive experiment to find out the specific influence of CE on LIF based vein recognition system.

For better understanding and comparing the influence of the referred CEs, we accordingly summarize the adopted CEs in SIFT based vein recognition system into three main groups: the first one refers to those focus only on the image itself and changing the pixel gray value by adopting linear/nonlinear function (LNFE); on contrast, the second one involves the effective and simple models based on the analysis of histogram information (HEs) while the third CE model improves the performance of HEs by adding transformations to the input subject of HEs so as to obtain better results with enhancement on useful detailed information (HEM), the specific grouping results could be referenced from Table 1.

To reliably evaluate the influence of CE on LIF, experiments of keypoints detection and matching in terms of SIFT is conducted with trial of eighteen CEs. However, to the best of our knowledge, there is no public hand-dorsa vein image database. Thus, a comprehensive database, CUMT Hand-Dorsa Vein Image Database is built and experimented. In our database, 2000 images were acquired from the left and right hands of 100 subjects covering male (students and teachers) and female (students and teachers). Ten different images from each hand represent ten different capturing conditions diverse in illumination, capturing time (morning, noon or afternoon), Fig. 2 illustrates samples of the lab-made database. Note that all the images used for CE and SIFT detection are the ROIs of the original ones, the specific ROI method is realized according to [3].

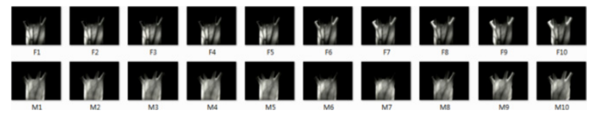


Fig. 2 Samples of the lab-made database (F: female, M: male).

2.1 Positive Effect on Keypoints Increase

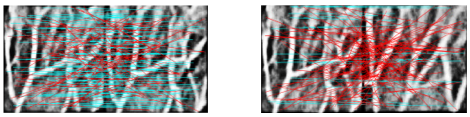
Apart from biometrical image, CE is reported to greatly increase the number of detected SIFT keypoints in all kinds of images. To analyze the specific increasing condition of all involved CEs on the lab-made vein data, all the eighteen CE methods are adopted directly on the ROI of the lab-made hand-dorsa vein images. The algorithm implementation of both CE and SIFT are available online. Due to the space limitation, we only record the statistical change, and the corresponding results are illustrated in Table 1.

Among the LNFE methods that we tested, UM yields the highest increase in the number of detected SIFT keypoints, with an average time of 7.6 for all the evaluated vein images no matter the hand or gender, followed by GLS with 5.4. Similar with LNFE methods, the HEs renders no great improvement on the number of detected keypoints with AHE achieves the highest one 28.1. Higher than majority of the former kinds of CE methods, HEM yields extraordinary increase, in which the highest with 39.9 and the lowest one with 5.8 respectively. Driven by in-depth analysis on the specific content evolution before and after CEs, the increase could be attributed to the fact that the image pixel values are re-mapped to a corresponding wider range of gray level values when the CEs are performed. As along with the range of pixel values increases, the probability that neighboring pixels of image with different values increases, and resulting in an increase in the possibility to identify scale-space extrema, followed by increase in the number of detected keypoints.

2.2 Negative Effect on Keypoints Matching

When focusing on the positive change with keypoints generation illustrated in Table 1, there is no doubt that the matching results would also be greatly boosted due to the increase in number of keypoints. However, it is reported in [2] that matching gradient based keypoint descriptors extracted from image sets preprocessed by CE is negatively affected in terms of Precision-Recall. As a result, an assumption is formed that the EER of SIFT based vein recognition system would also be affected in a similar way, which makes the results achieved in the public papers unconvincing, and the matching experimental results as illustrated in Fig. 3 and Table 2 verify the assumption.

Judging from the matching condition in Fig. 3 after adopting DHE for CE, it not only proves the conclusion reported in [2] but also figures out the infeasibility of the traditional SIFT based vein recognition system as illustrated in Fig. 1. The statistical matching results with all the involving



(a) (b)

Fig. 3 Matching results after DHE for contrast enhancement (red lines represent mismatching while cyan lines represent effective matching). (a) Intra-matching. (b) Outer-matching

Table 2 Influence of CEs on the Precision-Recall/Equal-Error-Rate of SIFT descriptor matching. Values represent variations of the PR/EER in respect to the value of the same metric in the absence of CE.

Model	LNFE				
	IN	GLS	GC08	CS	LS
PR	-2.88	-9.16	-1.98	-2.46	-2.41
EER	-0.94	-2.11	-0.52	-0.70	-0.82
Model	UM	HF	HBF	INE	
	-11.76	-1.21	-3.29	-1.07	
	-2.25	-0.52	-1.12	-0.34	
Model	HEs				
	HE	AHE	CLAHE	CLHE	
PR	-8.77	-23.36	-8.69	-8.11	
EER	-1.98	-5.14	-2.05	-1.91	
Model	HEM				
	IHE	DHE	HEHBF	RASF	HHE
PR	-15.07	-37.29	-9.19	-10.93	-18.59
EER	-6.20	-7.97	-2.39	-2.53	-6.95

CEs are illustrated in Table 2.

It should be noted firstly that the changing trend of PR and EER keep consistent with each other. Among the LNFE methods that we tested, UM yields the highest decrease in the descriptor matching of detected SIFT keypoints, with -11.76% and -2.25% for PR and EER respectively, followed by GLS with -9.16% and -2.11%. Unlike LNFE methods, both the HEs and HEM result in more severe decrease in the matching experiment. The HEM renders generally higher increase on the SIFT descriptors matching with DHE achieves the highest one -37.29% and -7.97%. A little bit lower than the HEM, HEs also yields extraordinary decrease, in which the highest with -23.36% and -5.14% while the lowest one with -8.11% and -1.91% respectively.

To take advantage of the increase in SIFT keypoints generation and remove the mismatching simultaneously, a hierarchical matching strategy is introduced to realize robust SIFT based vein recognition system. Note that the following experiments adopt DHE for CE due to its great performance in keypoints increase.

3. Hierarchical Mismatching Removal Strategy

To remove the mismatching efficiently and correctly, the hierarchical strategy with feature selection for non-vein keypoints removal and mirror matching strategy for unreliable matching removal is designed.

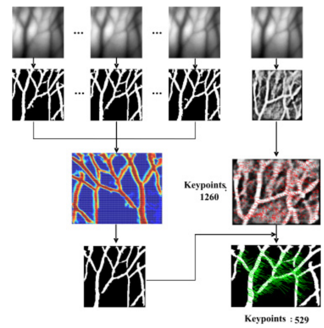
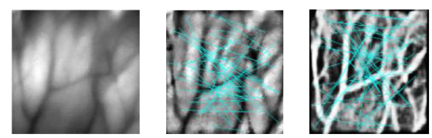


Fig. 4 Skeleton based SIFT feature selection procedure



(a) (b) (c)

Fig. 5 Evidence for the existence of mirror matching (only two representative CE methods are illustrated due to space limitation). (a) Original Vein image; (b) AHE; (c) DHE

3.1 Non-Vein Keypoints Removal

By observing the mismatching (Fig. 3) existed in both intra-matching and outer-matching, it could be observed that there exists many mismatched keypoints located in the non-vein parts, which is resulted from specific CE. To remove those non-vein matching, the vein skeleton is obtained and adopted for effective keypoints selection in the first removal stage, and the robust skeleton generation algorithm we design for the lab-made database is the same with the one we publish before, detailed information could be referenced from [3].

After obtaining the skeleton with the referenced segmentation algorithm, the feature selection template for each sample is generated by conducting 'AND' operation with ten samples of each subject. The whole selection procedure could be referenced from Fig. 4.

3.2 Mirror Matching Strategy

To remove all the possible mismatching sufficiently, the mirror matching strategy is designed as the second stage after the skeleton based feature selection system. The generation of mirror matching is inspired by a simple but novel idea: If a given feature points in one image is better matched with other points from the same vein image than points in the other one (as shown in Fig. 5), then any matches from this feature point to matching points in the other vein image are considered unreliable and should be discarded. The whole procedure of mirror matching is as shown in Fig. 6.

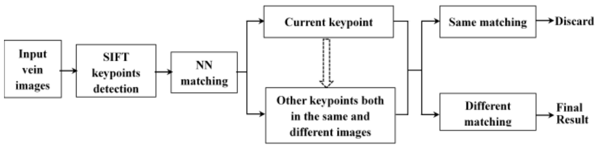


Fig. 6 Mirror matching framework

4. Matching Experiments and Analysis

4.1 Matching with SCIFM Strategy

The aim of the recognition experiment is to evaluate how well would the final performance be with improved SIFT model decreasing the negative influence brought by CEs, and the database is the same with the one in Part 2, Fig. 7 shows the mismatching removal effect of SCIFM.

It is obvious that the mismatching with red line both in IM and OM are all eliminated, and the preserved correct matching with cyan line are well preserved, which indicates a higher PR and EER value.

To fully demonstrate the effectiveness of the improved SIFT model tackling the negative effect of CEs, a comprehensive experiment by adopting all the CEs as the preprocessing method is realized and the corresponding result is as shown in Table 3.

By comparing the results in Table 3 with that in Table 2, the efficiency of the SCIFM strategy is fully verified. What's more, state-of-the-art recognition results by combining the specific CE method and the proposed SCIFM strategy fully demonstrates the effectiveness.

4.2 Comparison with State-of-The-Art Models

Two kinds of representative hand-crafted feature extraction algorithms are used as reference: The one is the local invariant feature model [4] including SIFT, SURF, ASIFT, RootSIFT, and it has the advantages of being invariant to rotation, translation, scale uncertainty and even nonuniform illumination, which makes it the best one among all hand-crafted algorithms (Note that all the models adopt DHE for contrast enhancement followed by direct extraction of keypoints and matching without the proposed mismatching removal). The other one is the LBP and its variants including LDP, LTP, and LLBP, and such model is widely applied for vein based identification application for its efficiency, and it also provides competitive recognition results.

Judging from EER result (as shown in Fig. 8) of verification with the lab-made database, it can be concluded that the improved matching model performs far better than the LIF models with EER as 0.061% whereas the best of LIF is 0.105% with RootSIFT and the best of LBPs is 0.113% with LDP, and the state-of-the-art identity recognition results fully demonstrate the ability of SCIFM strategy for improving the traditional SIFT based vein recognition systems, and we also argue that the proposed mismatching removal strategy could be adopted to improve the performance of other SIFT based image matching tasks.

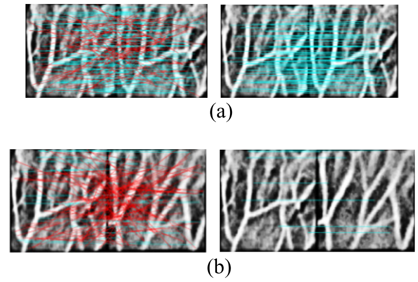
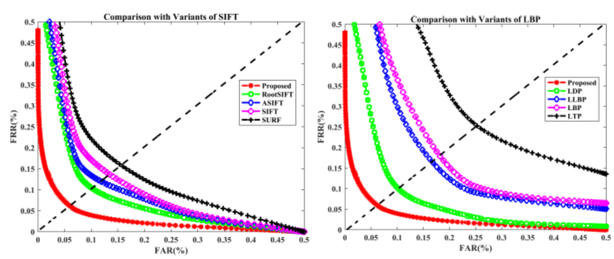


Fig. 7 Mismatching removal with the vein images enhanced by DHE. (a) Intra-matching. (b) Outer-matching

Table 3 EER value with SCIFM after different CEs

Model	LNFE				
	Original	IN	GLS	GC08	CS
EER(%)	18.4	15.589	9.8	17.302	15.604
Model	LS	UM	HF	HBF	INE
EER(%)	16.4	9.813	18.605	15.71	18.61
Model	HEs				
	HE	AHE	CLAHE	CLHE	
EER(%)	13.268	1.207	7.056	14.2	
Model	HEM				
	IHE	DHE	HEHBF	RASF	HHE
EER(%)	6.056	0.061	11.4	4.65	2.954



(a) (b)

Fig. 8 Comparison of ROC curves between SCIFM model and selected state-of-the-art hand-crafted methods (a: SIFTs, b: LBPs) (FAR: false acceptance rate, FRR: false rejection rate)

5. Conclusions

Vein recognition, one of the most promising personal identification patterns, faces the challenge that how to design robust feature representation model for building contact-free recognition system while making up for sparse structural information. SIFT, the most popular hand-crafted feature with good characteristics, is being adopted together with specific contrast enhancement to tackle the challenge with the published system as shown in Fig. 1, and state-of-the-art recognition results fully demonstrate its efficiency. However, conclusion in [2] drives me to challenge the credibility and efficiency of traditional model, and comprehensive experiments for evaluating both the positive and negative effect of CE on SIFT verify my query. To take advantage of the increase in

SIFT keypoints generation and remove the mismatching simultaneously, a hierarchical matching strategy, with which mismatching is removed thoroughly, is proposed by combing skeleton based feature selection for non-vein keypoints removal and mirror matching strategy for unreliable matching removal. State-of-the-art hand-dorsa vein recognition results fully demonstrate the effectiveness of the proposed model.

Acknowledgments

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