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Minutiae-based Finger Vein Recognition Evaluated with Fingerprint Comparison Software

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Abstract: Finger vein recognition is a biometric authentication technique based on the vein patterns of human fingers. Despite the fact that classical approaches are based on correlation, the topology of vein patterns allows the use of minutiae points for their representation. Minutiae points are the most used features for representing ridge patterns in fingerprints. In literature, it has been shown that minutiae can be used for finger vein comparison, but low image quality provokes that many spurious minutiae are extracted from them. In this work, a preprocessing method is presented, that combines classical digital image processing methods and level set theory in order to extract a set with the most reliable minutiae. The experiments were performed on two publicly available databases and different comparison methods were used for testing the representative character of the minutiae set extracted. The results showed that even though the amount of extracted minutiae is around 15-30, effective identification is possible.

Keywords: Finger veins, minutiae, recognition.

1 Introduction

Vascular pattern recognition, also called vein recognition, utilizing blood vessels located underneath the skin of a finger, hand, or wrist as a biometric trait has become an emerging technology in the field of biometrics. Under near-infrared (NIR) light the veins appear as dark structure which is captured on gray scale images with a NIR sensitive camera. The depicted vein structure is assumed to be unique for an individual, even for each hand or finger of a person [Uh20].

The veins are segmented using different methods, like *principal curvature* (PC) [Ch09], resulting in a binary vein pattern which is used as biometric template. The classical approach to compare two such templates is to obtain a similarity score by applying correlation. Another approach is to utilize intersection, branching or endpoints of the extracted vein pattern analogous to minutia points used in fingerprint recognition. Using minutiae points in vein recognition has already been investigated in literature. In [Yu09] and [WLC08] minutiae points are extracted from finger and hand vein images, respectively. For comparison of the biometric templates *modified Hausdorff distance* (MHD) is utilized in both cases. A similarity score between two minutiae sets from hands is calculated in [Ur11] by counting corresponding minutiae pairs that have similar relative positions and angles. In [Li14]

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minutiae pairing is done using SVD and the comparison is based on an average similarity degree after false pairs have been removed by applying a LBP variant locally. *Minutiae cylinder codes* (MCC) applied on hand vein minutiae points is described in [HTB13]. MCC has been originally introduced in fingerprint recognition [CFM10a].

The main contribution of this work is to show if it is possible to apply classical fingerprint minutiae comparison software on minutiae points extracted from vein images to achieve a high performance in accuracy and speed. To the authors best knowledge this has not been investigated in literature so far. For vein segmentation a novel method inspired by the general fingerprint minutiae extraction process is introduced, where some well known techniques for image processing with methods from level set theory are combined. From the experiments it can be seen, that despite the fact that the extracted minutiae set is small (25-30) it can correctly identify the vein pattern.

An advantage applying fingerprint minutiae comparison technology on vein images is, that there can be already existing solutions adopted to finger vein recognition, like for embedded systems or so called *Match-on-Card* (MoC) systems [BSV06], which would then be the first MoC system in finger vein recognition.

Four classical minutiae-based comparison software are evaluated, see section 3.

2 Proposed feature extraction

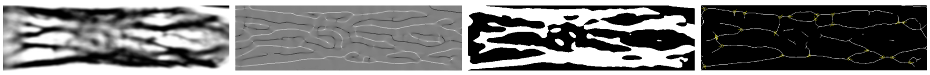
Inspired by the general idea for preprocessing fingerprint images with low quality, the following method is presented for extracting minutiae from finger vein images. The main idea is to extract the most reliable minutiae points. The method combines a group of well known techniques from digital image processing with methods from level set theory. For this, the vein image can be modeled as a fluid interface. Applications of fluid interfaces include breaking surface waves, in which factors such as topological connectivity and boundary conditions play significant roles [SS03].

The input image I is treated as a surface where each pixel is replaced by the curvature of the surface at that point. To calculate the curvature, a method based on level set theory [OS88] is used. This method has a positive impact on computational methods for surface movements and has been used to solve a wide kind of problems. In this method, the mean curvature δ of an image I is computed as $\delta = \nabla \cdot n$, where ∇ is the gradient operator and n is the outward drawn normal [Sm03] defined as $n = \frac{\nabla_I}{|\nabla_I|}$.

By resting in this theory for detecting the ridges and valleys location, and by using well known methods from literature [GW06] for enhancing the image, the method for extracting minutiae points is introduced and it is explained below. A visual example of the method output is presented in figure 1.

Due to the low quality presented in vein image, first the image has to be smoothed. In order to reduce the pixelation effect during capturing, the mask size which must to be used in this case is small. The images usually present very low contrast in all the dimensions. Even in some cases, there is not a visual difference between finger veins and the background. Therefore, a process of image normalization is needed. After normalizing the image, it will be distorted. This process may cause the appearance of some spurious artifacts. An oriented contextual filtering can enhance the image and it can highlight the truly vein pattern structure. The orientation field is calculated by using the classic gradient method from

literature [Ma09], in this case, the window (w_θ) for processing the image needs to be selected from a small set of possible values. The filtering stage is done with a bank of 120 low-pass oriented filters.
The binarization process is not trivial. In fingerprints, ridges and valleys have similar dimensions, and the threshold can be determined by local average. For vein images, this process is not appropriate, because ridges and valleys have different width. So, it is necessary to calculate the highest values for ridges and the lowest values for valleys. For this purpose, by relying on level set theory, the normalized gradient divergence is calculated, in order to highlight the maximum and minimum peaks in the image. Maximum peaks have a positive value, minimum peaks have a negative value and the ones that are not peaks have values close to 0. For identifying these peaks, Otsu thresholding is applied to the absolute value of the normalized gradient divergence. Then, these peaks are used to estimate a reliable local threshold for binarizing the image. For this purpose, the size of the windows for smoothing the image before calculating the divergence (w_δ) and for binarizing the image (w_β) need to be estimated. After binarization, the skeleton image is calculated and minutiae are extracted with well known methods from literature [ZS84]. Only bifurcations are selected, because endings are very probably spurious minutiae. For calculating a reliable minutiae direction, bifurcations where the length of at least one of their branches is less than a certain threshold (γ_{min}) are eliminated. Also, the length of each branch line (λ) where the trace is going to stop for calculating direction needs to be declared. Direction field for each minutiae is calculated in the same way as for fingerprint minutiae.



(a) (b) (c) (d)

Fig. 1: Example image from the UTFVP database showing the main steps of the method process. (a) The enhanced image with the oriented contextual filter. (b) The normalized gradient divergence. (c) The binarized image. (d) Vein skeleton with the extracted minutiae.

3 Experiments

The experiment's main purpose is to show that finger vein patterns can be correctly described by a small minutiae set, corroborating in this way, the idea of using minutiae points for finger vein recognition.
The following four fingerprint minutiae comparison software packages are used: The publicly available Bozorth3 as a part of the NIST Biometric Image Software (NBIS) Release 5.0.0 and the Minutiae Cylinder Code (MCC) SDK [Ca10, CFM10b], as well the IDKit SKD Version 9.0 from Innovatrics and the VeriFinger 11.2 Extended SDK from Neurotechnology, two commercial products. Latter both offer a MoC system which is NIST Minutiae Interoperability Echange (MINEX) compliant. MHD is used as an additional point based comparison method.
To compare the minutiae-based approaches to classical vein recognition techniques, PC has been chosen, which shows a good baseline performance in vein recognition. PC is a vein segmentation method and cross-correlation is used to obtain a similarity score between two templates [Ch09].

IDKit and VeriFinger require the minutiae input in the ANSI/INCITS 378-2004 [AN04] binary format, MCC can read the minutiae from ASCII files. All three use the information of image size and resolution. Some tests showed, that different comparison scores are produced when the resolution value changes, which is true for all three software packages. Therefore, a resolution value is chosen such that the vein image ROI has approximately the same size as the bounding box of a fingerprint with a resolution of 500 dpi. For the UTFVP ROIs (336×128 pixels) a resolution of 134 pixel per centimeter (pcc) and for the PLUS ROIs (368×96 pixels) a resolution of 147 pcc is derived.
The proposed preprocessing method was implemented in Matlab 2019. MHD and PC as well the comparison score evaluation have been implemented in C++ using the OpenCV library version 3.4.2.

3.1 Data sets

Two publicly available finger vein data bases are used for the experiments:

- The *University of Twente Finger Vascular Pattern Database* (UTFVP)[TV13] contains images of six fingers (index, middle and ring finger) of both hands of 60 subjects. Four samples of each finger have been acquired.
- The *PLUSVein-FV3 Finger Vein Database* [KPU18] (PLUS) contains 4 data sets of the same subjects and fingers with images captured from the dorsal (D) and palmar (P) view, both acquired with LED and Laser illumination, respectively. It also provides already extracted ROI images which were used in the experiments.

3.2 Parameter search

The quality of the extracted features highly depends on the image quality. Therefore, the parameter selection for the method is crucial. Databases have different acquisition characteristics and quality of the obtained data varies from one database to another. Therefore, a parameter search is needed for obtaining the best possible results.
To avoid over fitting a 2-fold validation is employed, splitting the data in such a way, that each fold contains the images from half of the subjects which are assigned to each fold randomly. For each parameter set the *equal error rate* (EER) is calculated for each fold. Based on the lowest EER value found in fold 1, the comparison scores of a parameter set in fold 2 are selected and vice versa, then they are combined and on them again the EER is evaluated and reported. This is done 100 times, each time splitting the subjects randomly.
For the preprocessing and feature extraction method the parameter value search is performed on a total of 5 parameters. The possible values for each of these parameters are selected by studying each step involved in the entire process. The combinations of all parameters make a total of 144 different settings: $w_\theta \in \{8,16,32\}$, $w_\delta \in \{4,8,12,16\}$, $w_\beta \in \{32,40,64\}$, $\gamma_{min} \in \{10,20\}$ and $\lambda \in \{10,20\}$.

In case of the MCC SDK also a parameter search is necessary. After investigating the behavior of different MCC settings for fingerprint tenprint impressions and fingerprint latent impressions [Ca10, CFM10b], some parameters were set based on previous researches for latent fingerprints [VMM19] and for some of them a set of possible values was selected. Due to the high amount of possible parameter settings, first a parameter search was done only for one minutiae set of the UTFVP database (total of 1527 parameter combinations). Then the parameters of the first 50 best results have been investigated and a subset has been chosen for enrollment: $radius = 300, \sigma_s = 9, \sigma_d = \frac{\pi}{6}, \mu_\psi = 0.002, \omega = 100, Min_{VC} = 0.03, Min_M = 1$ and for comparison: $Min_{ME} = 0.03, \delta_t = \frac{\pi}{6}, \mu_P = 32, \mu_{\rho 1} \in \{\frac{1}{30}, \frac{1}{24}\}, \tau_{\rho 1} \in \{-50, -100\}, \mu_{\rho 2} \in \{\frac{\pi}{8}, \frac{\pi}{4}\}, \tau_{\rho 2} = -25, \mu_{\rho 3} = \frac{\pi}{16}, \tau_{\rho 3} \in \{-28, -40\}, nrel = 4$.

3.3 Evaluation

Evaluation is done applying the fingerprint verification competition 2006 [3] (FVC) protocol and each finger of an individual is considered as a single class. Next to the recognition accuracy, execution times for the template comparison have been evaluated, to show differences in time performance between minutiae-based and the classical correlation-based finger vein recognition methods. All templates are loaded into RAM so that only template comparison time is considered. The time needed to execute 66780 comparisons has been measured (UTFVP dataset following FVC protocol).

3.4 Results

Table 1 - 5 report the recognition performance for the used data sets and different methods applied on them. For all reported values the average (avg) as well the standard deviation (std) have been calculated using the results of the $N = 100$ different evaluations as described in section 3.2. For the EER additionally the minimum and maximum value of the 100 fold splits is presented to show how much the performance can vary depending on the selection of subjects for the parameter estimation. Beside EER, the ZeroFMR, FMR100, ZeroFNMR, FNMR100 and *area under curve* (AUC) are reported.
In general, the four minutiae-based comparison software SDKs Bozorth3, IDKit, VeriFinger and MCC perform quite similar, being VeriFinger the one which obtains the best results. On the PLUS data sets MCC lies very close to VeriFinger and IDKit, while on the UTFVP database its performance is a little bit lower and is similar to Bozorth3. MHD, which is a more naive approach, clearly shows the lowest performance on all data sets. The classical correlation-based PC shows a better performance on all databases.
The results indicate, that on the dorsal view of a finger a better performance can be achieved. It seems there are more structures visible which are feasible for minutiae extraction. Table 6 shows the evaluation of the execution times for 66780 comparisons, averaged over 10 runs. It clearly shows that all minutiae-based approaches run almost two order of magnitude faster than the classical correlation-based PC approach.

[3] http://bias.csr.unibo.it/fvc2006/perfeval.asp

Tab. 1: Recognition performance for the UTFVP data set.

UTFVP	EER in%				ZeroFMR in%		FMR100 in%		ZeroFNMR in%		FNMR100 in%		AUC in%	
	avg	std	min	max	avg	std	avg	std	avg	std	avg	std	avg	std
Bozorth3	12.1	0.4	11.5	13.4	57.3	5.8	25.2	0.8	91.1	1.4	89.6	1.3	93.85	0.33
IDKit	10.1	0.3	9.6	10.9	47.8	8.6	19.0	0.6	98.8	0.1	77.9	2.7	95.49	0.19
VeriFinger	6.8	0.2	6.4	7.2	39.0	4.2	15.5	0.5	11.0	0.1	11.0	0.1	96.41	0.29
MHD	14.7	0.4	13.8	15.8	72.5	5.0	34.4	1.2	99.7	0.3	87.3	2.3	92.50	0.30
MCC	12.2	0.4	11.6	13.4	51.8	5.3	22.9	0.8	99.3	0.5	88.0	2.5	93.88	0.28
PC	0.4	0.1	0.2	0.8	1.2	0.5	0.3	0.1	85.0	10.2	0.0	0.1	99.86	0.05

Tab. 2: Recognition performance for the PLUS-Las-P data set.

PLUS-Las-P	EER in%				ZeroFMR in%		FMR100 in%		ZeroFNMR in%		FNMR100 in%		AUC in%	
	avg	std	min	max	avg	std	avg	std	avg	std	avg	std	avg	std
Bozorth3	12.4	0.3	11.8	13.2	63.9	10.8	22.2	0.5	17.3	0.8	17.3	0.8	88.72	0.54
IDKit	8.2	0.3	7.7	9.1	58.1	7.5	14.2	0.5	99.4	0.0	83.6	2.3	96.25	0.20
VeriFinger	6.5	0.2	6.0	7.0	58.0	10.1	13.0	0.8	9.1	0.2	9.1	0.2	95.01	0.37
MHD	25.8	32.4	10.9	100.0	71.3	13.9	39.3	26.6	99.9	0.1	90.8	4.5	79.32	34.68
MCC	9.2	0.2	8.7	9.7	50.3	9.0	16.1	0.5	99.9	0.1	87.1	2.7	95.74	0.15
PC	1.3	0.3	1.0	2.5	3.9	1.1	1.3	0.4	92.1	7.4	4.5	6.1	99.67	0.13

Tab. 3: Recognition performance for the PLUS-Las-D data set.

PLUS-Las-D	EER in%				ZeroFMR in%		FMR100 in%		ZeroFNMR in%		FNMR100 in%		AUC in%	
	avg	std	min	max	avg	std	avg	std	avg	std	avg	std	avg	std
Bozorth3	7.5	0.3	6.9	8.6	36.1	7.5	12.2	0.7	25.9	2.9	25.9	2.9	94.93	0.35
IDKit	3.7	0.2	3.2	4.3	36.2	7.7	5.3	0.4	99.7	0.9	44.5	4.3	98.80	0.09
VeriFinger	3.1	0.1	2.9	3.5	23.8	4.7	4.4	0.3	9.0	0.1	9.0	0.1	98.13	0.14
MHD	9.8	3.8	0.1	16.7	56.2	13.1	20.4	7.0	100.0	0.1	77.9	14.8	95.39	2.73
MCC	3.9	0.2	3.4	4.6	23.1	4.4	5.6	0.4	100.0	0.0	54.0	6.6	98.58	0.13
PC	0.4	0.1	0.2	0.8	1.7	0.7	0.3	0.1	43.6	34.5	0.0	0.0	99.97	0.02

4 Conclusion

In this work a novel method for extracting minutiae points from finger vein patterns is introduced. This method uses techniques from level set theory for detecting the reliable ridges and valleys from the vein pattern. For evaluating the extraction process the performance of some classical minutiae-based fingerprint comparison techniques are reported. Two state of the art commercial and two publicly available comparison software packages were used. The results achieved by the minutiae-based comparison techniques show promising performances. Although the classical correlation-based PC approach obtains the best results in terms of recognition accuracy, when it comes to the processing time of the comparisons it clearly shows its weakness compared to the minutiae-based comparison methods. The experiments show that there is a trade-off between accuracy and comparison speed using minutiae-based approaches or classical techniques. In future work the binarization process should be enhanced. In this way, more reliable ridges can be detected. Therefore, less minutiae will be missed and less spurious minutiae will be extracted.

Tab. 4: Recognition performance for the PLUS-Led-P data set.

PLUS-Led-P	EER in%				ZeroFMR in%		FMR100 in%		ZeroFNMR in%		FNMR100 in%		AUC in%	
	avg	std	min	max	avg	std	avg	std	avg	std	avg	std	avg	std
Bozorth3	10.6	0.4	10.0	12.4	49.2	5.3	19.8	0.5	23.8	0.8	23.8	0.8	91.60	0.41
IDKit	6.8	0.3	6.4	7.6	40.5	6.4	11.7	0.5	100.0	0.0	71.5	4.2	97.17	0.20
VeriFinger	5.4	0.2	5.0	5.9	35.4	6.9	10.2	0.4	10.1	0.1	10.1	0.1	96.55	0.21
6 MHD	18.4	2.9	10.7	23.7	73.6	7.2	39.7	5.2	100.0	0.1	96.7	3.2	88.43	2.58
MCC	8.4	0.2	7.9	8.9	46.1	6.7	14.8	0.5	100.0	0.0	87.2	2.3	96.16	0.16
PC	0.8	0.1	0.5	1.6	2.8	1.0	0.7	0.2	72.7	24.0	0.4	0.5	99.89	0.05

Tab. 5: Recognition performance for the PLUS-Led-D data set.

PLUS-Led-D	EER in%				ZeroFMR in%		FMR100 in%		ZeroFNMR in%		FNMR100 in%		AUC in%	
	avg	std	min	max	avg	std	avg	std	avg	std	avg	std	avg	std
Bozorth3	7.0	0.4	6.4	8.2	33.0	3.9	11.3	0.6	29.2	1.3	29.2	1.3	95.33	0.41
IDKit	3.7	0.3	3.2	4.9	34.2	12.6	5.6	0.5	96.6	2.5	39.0	4.6	98.91	0.12
VeriFinger	3.2	0.2	2.8	3.8	22.5	5.5	4.9	0.3	9.5	0.2	9.5	0.2	98.22	0.24
MHD	14.4	4.7	7.1	21.6	58.9	8.3	28.1	8.7	99.7	0.6	89.1	11.8	91.66	3.80
MCC	4.3	0.2	3.9	4.9	27.0	6.3	6.4	0.3	99.7	0.4	55.8	4.2	98.46	0.13
PC	0.3	0.1	0.2	0.4	1.0	0.4	0.2	0.1	38.9	29.0	0.0	0.0	99.98	0.01

Tab. 6: Execution times of 66780 template comparisons.

	VeriFinger	MCC	MHD	PC
Time in sec	30.6 ± 0.6	45.7 ± 0.1	17.3 ± 0.2	1678.8 ± 61.7

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References

[AN04] ANSI-INCITS 378-2004: , Information Technology - Finger Minutiae Format for Data Interchange, 2004.

[BSV06] Bistarelli, Stefano; Santini, Francesco; Vaccarelli, Anna: An Asymmetric Fingerprint Matching Algorithm for Java Card TM. Pattern Anal. Appl., 9(4):359–376, Oct. 2006.

[Ca10] Cappelli, Raffaele; Ferrara, Matteo; Maltoni, Davide; Tistarelli, Massimo: MCC: A baseline algorithm for fingerprint verification in FVC-onGoing. In: 11th Int. Conf. on Control, Automation, Robotics and Vision, ICARCV 2010, Singapore, 7-10 December 2010, Proc. pp. 19–23, 2010.

[CFM10a] Cappelli, R.; Ferrara, M.; Maltoni, D.: Minutia Cylinder-Code: A New Representation and Matching Technique for Fingerprint Recognition. IEEE Trans. on Pattern Analysis and Machine Intelligence, 32(12):2128–2141, Dec 2010.

[CFM10b] Cappelli, Raffaele; Ferrara, Matteo; Maltoni, Davide: Minutia Cylinder-Code: A New Representation and Matching Technique for Fingerprint Recognition. IEEE Trans. Pattern Anal. Mach. Intell., 32(12):2128–2141, 2010.

[Ch09] Choi, Joon Hwan; Song, Wonseok; Kim, Taejeong; Lee, Seung-Rae; Kim, Hee Chan: Finger vein extraction using gradient normalization and principal curvature. In (Niel, Kurt S.; Fofi, David, eds): Image Processing: Machine Vision Applications II. volume 7251. Int. Society for Optics and Photonics, SPIE, pp. 359 – 367, 2009.

[GW06] Gonzalez, Rafael C.; Woods, Richard E.: Digital Image Processing (3rd Edition). Prentice-Hall, Inc., USA, 2006.

[HTB13] Hartung, D.; Tistarelli, M.; Busch, C.: Vein minutia cylinder-codes (V-MCC). In: 2013 Int. Conf. on Biometrics (ICB). pp. 1–7, June 2013.

[KPU18] Kauba, Christof; Prommegger, Bernhard; Uhl, Andreas: The Two Sides of the Finger - An Evaluation on the Recognition Performance of Dorsal vs. Palmar Finger-Veins. In: Proc. of the Int. Conf. of the Biometrics Special Interest Group (BIOSIG'18). Darmstadt, Germany, pp. 1–8, 2018.

[Li14] Liu, Fei; Yang, Gongping; Yin, Yilong; Wang, Shuaiqiang: Singular value decomposition based minutiae matching method for finger vein recognition. Neurocomputing, 145:75 – 89, 2014.

[Ma09] Maltoni, Davide; Maio, Dario; Jain, Anil K.; Prabhakar, Salil: Handbook of Fingerprint Recognition. Springer Publishing Company, Incorporated, 2nd edition, 2009.

[OS88] Osher, Stanley; Sethian, James A.: Fronts Propagating with Curvature Dependent Speed: Algorithms Based on Hamilton-Jacobi Formulations. Journal of computational physics, 79(1):12–49, 1988.

[Sm03] Smereka, Peter: Semi-Implicit Level Set Methods for Curvature and Surface Diffusion Motion. Journal of Scientific Computing, 19:439–456, 2003.

[SS03] Sethian, J. A.; Smereka, Peter: Level Set Methods for Fluid Interfaces. Annual Review of Fluid Mechanics, 35(1):341–372, 2003.

[TV13] Ton, B. T.; Veldhuis, R. N. J.: A high quality finger vascular pattern dataset collected using a custom designed capturing device. In: 2013 Int. Conf. on Biometrics (ICB). pp. 1–5, June 2013.

[Uh20] Uhl, Andreas; Busch, Christoph; Marcel, Sebastien; Veldhuis, Raymond: Handbook of Vascular Biometrics. Advances in Computer Vision and Pattern Rec. Springer Nature Switzerland AG, Cham, Switzerland, 2020.

[Ur11] Uriarte-Antonio, J.; Hartung, D.; Pascual, J. E. S.; Sanchez-Reillo, R.: Vascular biometrics based on a minutiae extraction approach. In: 2011 Carnahan Conf. on Security Technology. pp. 1–7, Oct 2011.

[VMM19] Valdes-Ramirez, Danilo; Medina-Pérez, Miguel Angel; Monroy, Raúl: Stacking Fingerprint Matching Algorithms for Latent Fingerprint Identification. In: Progress in Pattern Rec., Image Analysis, Computer Vision, and Applications - 24th Iberoamerican Congress, CIARP 2019, Havana, Cuba, Oct. 28-31, 2019, Proc. pp. 230–240, 2019.

[WLC08] Wang, Lingyu; Leedham, Graham; Cho, David Siu-Yeung: Minutiae feature analysis for infrared hand vein pattern biometrics. Pattern Rec., 41(3):920 – 929, 2008. Part Special issue: Feature Generation and Machine Learning for Robust Multimodal Biometrics.

[Yu09] Yu, Cheng-Bo; Qin, Hua-Feng; Cui, Yan-Zhe; Hu, Xiao-Qian: Finger-vein image recognition combining modified Hausdorff distance with minutiae feature matching. Interdisciplinary Sciences: Computational Life Sciences, 1(4):280–289, Dec 2009.

[ZS84] Zhang, T. Y.; Suen, C. Y.: A Fast Parallel Algorithm for Thinning Digital Patterns. Commun. ACM, 27(3):236–239, March 1984.