A. Brömme, C. Busch, N. Damer, A. Dantcheva, M. Gomez-Barrero, K. Raja,
C. Rathgeb, A. Sequeira, and A. Uhl (Eds.): BIOSIG 2021,
Lecture Notes in Informatics (LNI), Gesellschaft für Informatik, Bonn 2021

On the Relevance of Minutiae Count and Distribution for Finger Vein Recognition Accuracy

Michael Linortner[1], Andreas Uhl[1]

Abstract: Vein recognition usually uses binary features, but besides deep learning-based approaches key-point and minutiae-based ones started to become popular as well. Statistical measures for vein minutiae points, like spatial point distribution, have not been investigated in literature so far. In this work the number of vein minutiae points and their spatial distribution is analyzed in relation to recognition accuracy. The goal is to initiate a discussion on statistical behavior of vein minutiae points and deriving possible quality measures for vein minutiae point sets.

Keywords: Vein recognition, vein minutiae distribution, spatial point distribution.

1 Introduction

Finger or hand vein recognition has become an established and accepted technology in biometrics. One approach is to use branches of the blood vessels as minutiae points analogously to minutiae points in fingerprint recognition. Due to low image quality of the raw sample images, a crucial step is the parameter selection for the feature extraction process, consisting of preprocessing, image enhancement and vein segmentation. Varying these parameters alters the segmented vein output from which minutiae points are extracted. As a consequence, the minutia sets may vary. In literature there is no generally accepted approach to derive optimal parameters for vein minutiae extraction and there is no accepted and standardized quality measure for vein images with respect to minutiae-based vein recognition. It is of interest to gather knowledge on how variations in the minutiae sets influence the recognition accuracy. The first aspect worth investigating is the impact of the number of minutia points on the recognition performance. Further it is of interest to learn about the minutiae's spatial point distribution, whether they follow spatial randomness, tend to disperse or to cluster and hence, the influence on the recognition accuracy. Knowledge about minutia point distribution is a key aspect in biometric individuality studies. For fingerprint minutiae points there exists corresponding literature, for example [Bo04, Sc79, PPJ01, JY06].

For vein minutiae no statistical investigations regarding number of minutiae and minutiae point distribution have been done so far. The goal of this work is to initiate a discussion on statistical behavior of vein minutiae points and deriving possible quality measures for vein minutiae extraction. Therefore, the relation between the number of vein minutiae points and recognition accuracy is analyzed. To determine spatial distribution of minutiae points, two measures are employed, which characterize the spatial distribution of minutiae points

[1] Department of Computer Sciences, University of Salzburg, Salzburg, Austria, {mlinortner,uhl}@cs.sbg.ac.at

in a single number. These numbers are set in context to the recognition performance and the number of minutiae points to reveal potential correlations.
In a previous work [LU21] we showed that utilizing finger vein minutiae points in combination with standard minutiae-based fingerprint recognition software can compete with and even outperform classic vein recognition techniques in terms of recognition accuracy and comparison time, which motivates this work to analyze statistical behavior of finger vein minutiae points.

2 Methods

Two distance-based point pattern measures are utilized to describe the spatial point distribution of vein minutia points. Let M denote a (minutiae) point set containing n points p, U_{ij} a set containing the Euclidean distances $d(p_i, p_j)$ of each point $p_i, p_j \in M$, $i \neq j$ and the mean nearest neighbor distance $\bar{d}_{\min}$ with $\bar{d}_{\min} = \frac{1}{n}\sum_{i=1}^{n}\min\{U_{ij}\}$. The overall density λ of a point pattern can be estimated with $\hat{\lambda} = n/A$, where $\hat{\lambda}$ is the estimated intensity, n the number of points in M within a region of area A. Under assumption of complete spatial randomness (CSR) the expected value for $\bar{d}_{\min}$ is $E(d) = \frac{1}{2\sqrt{\lambda}}$. Thus, a ratio R can be defined [OU10]:

$$R = \frac{\bar{d}_{\min}}{0.5\sqrt{A/n}} \tag{1}$$

describing a pattern's point distribution relative to CSR. An R value < 1 indicates a tendency towards clustering and > 1 towards dispersing, respectively.
The second measure utilizes the K-function $K(t)$, which incorporates all distances between a point and its neighbors within a radial distance t. The estimator for $K(t)$ is defined as follows [Di14]:

$$\hat{K}(t) = \frac{A}{n(n-1)}\sum_{i=1}^{n}\sum_{i \neq j}\frac{1}{w_{ij}} I(U_{ij} < t) \tag{2}$$

with $I(\cdot)$ as indicator function and w_{ij} computed as in equations (4.16) and (4.17) in [Di14]. The variance $v_{LS}(t)$ of $\hat{K}(t)$ is computed as in equation (4.19) in [Di14]. The expected value of $K(t)$ under CSR is πt^2 and the difference is given with $D(t) = \hat{K}(t) - \pi t^2$. $D(t) > +2\sqrt{v_{LS}(t)}$ indicates clustering, $D(t) < -2\sqrt{v_{LS}(t)}$ indicates dispersion whereas in between the CSR assumption holds [Di14]. $D(t)$ has been used in [JY06] to investigate the distribution of fingerprint minutiae points. In this work we use

$$Q = F\left(D(t), +2\sqrt{v_{LS}(t)}), t_{\min}, t_{\max}\right) \tag{3}$$

as our second measure to describe the minutiae point distribution in a single number. $F(\cdot)$ computes the area between $D(t), +2\sqrt{v_{LS}(t)})$ in the interval $t \in [t_{\min}, t_{\max}]$. Thus, Q gives a measure for the tendency to cluster.

3 Experiments

The experiments are conducted on four publicly available finger vein data sets: the UTFVP data set [TV13], containing 1440 images from 360 fingers, the HKPU-FV data set (1. session) [KZ12], containing 1872 images from 312 fingers and two data sets of the PLUS-3FV database [KPU18] each consisting of 1880 images from 360 fingers captured under near-infrared laser illumination. One data set shows the palmar view of the finger and the other the dorsal view. They are denoted a PLUS-Las-P and PLUS-Las-D, respectively.
Four standard minutiae-based fingerprint recognition tools are utilized to compute the recognition accuracy for each setting, expressed as equal error rate (EER): two publicly available tools, the Bozorth3 as part of the NIST Biometric Image Software (NBIS) Release 5.0.0[2] and the minutiae cylinder code (MCC) SDK [CFM10, CFM11, FMC12, FMC14], as well as two state of the art commercial products, the IDKit SDK Version 9.0[3] and the VeriFinger 11.2 Extended SDK[4]. As these tools are design for fingerprint recognition they are not suitable to retrieve minutiae points from finger vein images, but their minutiae-based comparison algorithms are utilized. Therefore, the vein minutiae points are extracted as proposed in [LU21] and stored in a standardized format, in order to be usable for the comparison algorithms in the above mentioned fingerprint recognition tools. Briefly summarized, the minutiae points in [LU21] are extracted by firstly applying image enhancement on the a vein sample. Then the veins are segmented, subsequently thinned and from the resulting skeleton bifurcation points are retrieved which serve as minutiae points. On each data set 308 different parameter settings are applied to extract a variation of minutiae sets. The parameters for image enhancement, vein segmentation and spur removal in the thinning process are modified and the combinations of all selected parameter values generate 308 different settings, where each individual setting produces a single set of minutiae points on which in the following the statistical analysis is performed. We use the same parameter settings as in [LU21] (ergo the same minutiae points), extended by additional parameter settings to retrieve additional minutiae sets with a lower number of minutiae points in average to extend the variability. As in [LU21] the results in terms of recognition accuracy show it is suitable to utilize finger vein minutiae points in combination with minutiae-based fingerprint comparison software as a biometric recognition technique. Therefore, it motivates to investigate the extracted minutiae points regarding correlations between number or distribution and recognition performance employing the proposed measures. For more detailed information on utilizing finger vein minutiae points in combination with standard fingerprint recognition tools and the performance in recognition accuracy and template comparison time, also related to standard vein recognition techniques, the interested reader is referred to [LU21].

On each minutiae set three indicators are investigated: the number of minutiae points, mean nearest neighbor ratio R and Q, all in relation to the EER. To compute a single value for each setting representing the whole data set, for each indicator the average is computed over all vein samples in a data set. Thus, the mean number of minutiae points per sample is computed with $1/N \sum_i |M_i|$, with N as the number of samples in a data set and $|M_i|$ as the

[2] https://www.nist.gov/services-resources/software/nist-biometric-image-software-nbis
[3] https://www.innovatrics.com
[4] https://www.neurotechnology.com/verifinger.html

amount of minutiae points in a sample i. The mean nearest neighbor ratio is computed with $\bar{R} = 1/N \sum_i R_i$, applying equation (1) on M_i to obtain R_i and $\bar{Q} = 1/N \sum_i Q_i$ by applying equation (3) on M_i to obtain Q_i. The parameter t is varied between 0 and $\min(a,b)/4$ where a and b describe the width and height of the finger vein region of interest (ROI) from which the minutiae points have been extracted.

4 Results

Figure 1 shows a minutiae point density map for each data set averaged over all containing image samples exemplary using the parameter configuration leading to extracted minutiae points on which VeriFinger performs best. It visualizes how densely minutiae points populate certain areas of the used finger vein ROI. Therefore, the ROI region is tiled into bins of size 4×4 pixels and a density histogram is computed. The visual impression suggests that the minutiae points are somehow randomly distributed, but especially on the PLUS-Las and HKPU-FV data sets a tendency for clustering in certain areas can be observed. There are noticeable differences between the minutiae point density maps of the different data sets.

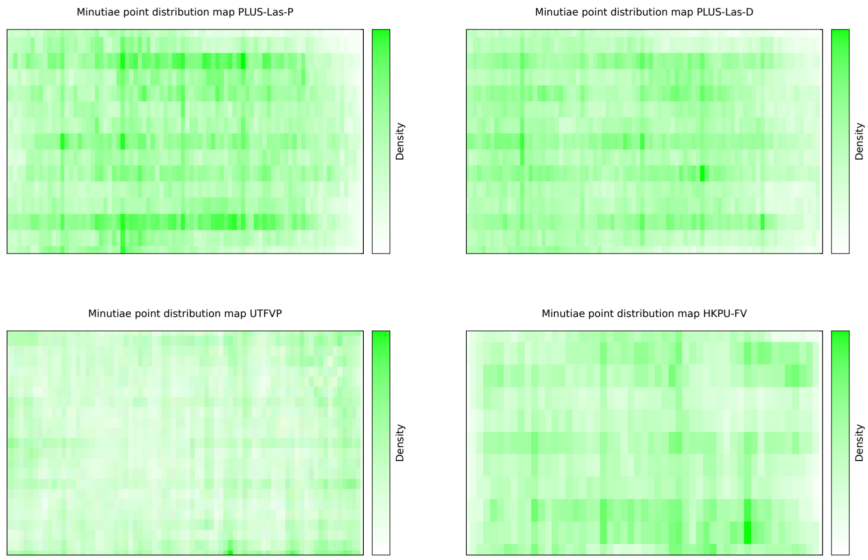


Fig. 1: Density map of vein minutiae points within the utilized finger ROI.

Figure 2 shows the relation between recognition performance and mean amount of minutiae points per finger vein sample. On the PLUS data set the behavior is as expected: there is a range, between 40 to 60 minutiae points per sample, where the recognition methods perform best, while with a increasing or decreasing number of points the recognition performance decreases. Having too few minutiae points means that important information is lost. On the other end, if there are too many false and noisy minutiae points included it

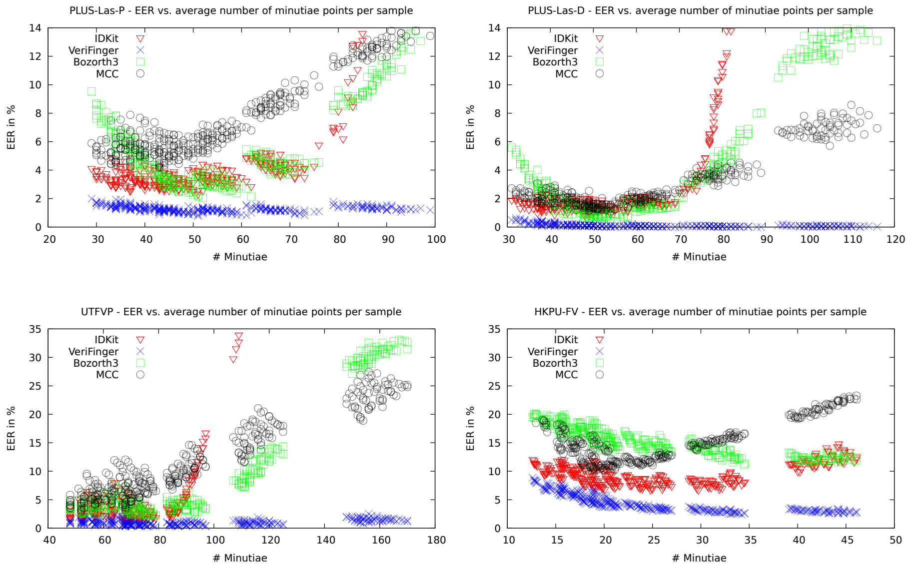


Fig. 2: EER vs. average number of minutiae points per vein sample.

causes a drop in recognition accuracy. Interestingly, VeriFinger is able to maintain high recognition accuracy with an increasing number of minutiae. On the UTFVP data set it was not possible to extract minutiae sets which contain less than 40 minutia points per sample on average, so we can only see the trend of decreasing EER with an increasing number of points. The HKPU-FV is a challenging data set for minutiae-based methods. Compared to the other data sets the samples' image quality is lower, often parts of a finger are overexposed and without visible vein structure. VeriFinger and Bozorth3 show a clear trend of increasing recognition accuracy towards 40 and more minutiae per sample, while for IDKit and MCC the optimum is around 20 minutiae points for the HKPU-FV data set.

In figure 3 the relation of the mean nearest neighbor ratio $\bar{R}$ to the EER is plotted. First we can observe that for the PLUS data sets there a is general tendency towards clustering ($\bar{R} < 1$). The EER decreases with increasing $\bar{R}$ which could indicate that randomly distributed minutiae points are better for the recognition accuracy than clustered points. For the UTFVP data set it can be stated that the points in all extracted minutiae sets are randomly distributed because $\bar{R}$ varies within a narrow range around 1. This suggests, that the trend visible in the plot is most likely caused by the amount of minutiae point rather than by the distribution. On the HKPU-FV data set the minutiae points slightly tend to disperse.

The relation between the third measure $\bar{Q}$ and EER is visualized in figure 4. It can bee seen that for each data set every single setting produces minutiae sets which, on average, show some clustering. Note that it is no contradiction to the results produced by measuring $\bar{R}$, where it is indicated that there are settings which generate on average randomly distributed minutia sets ($\bar{R} = 1$). $\bar{R}$ is a global measure on a point set, while $D(t)$ operates on different scales (by varying t) and can detect local clusters even when on global scale the distribution

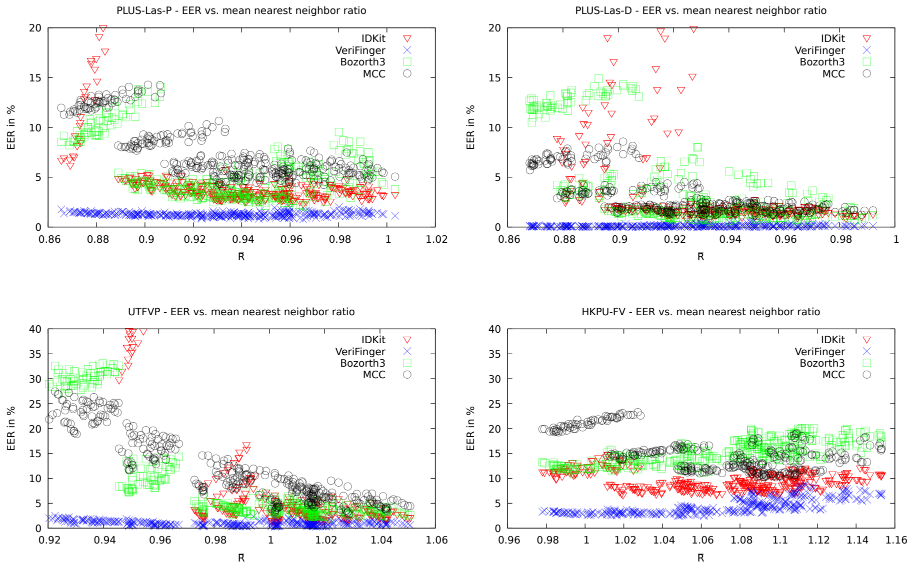


Fig. 3: EER vs. $\bar{R}$.

is closer to random. Clustering at any scale is accumulated in $\bar{Q}$. The standard deviation of Q is around 2 times $\bar{Q}$ which indicates that in a data set there are minutiae sets which do not cluster and others may cluster considerably. VeriFinger's recognition performance shows a clear trend of dropping with increasing $\bar{Q}$ (more clustering). On the PLUS data set there are more outliers for the other recognition methods but those settings which produce the best recognition accuracy follow the same trend as VeriFinger. On the UTFVP data set the $\bar{Q}$ values of the MCC methods are more scattered, but they indicate that for a low EER the $\bar{Q}$ value needs to be small.

To investigate whether there is a correlation between the average minutiae count and the distribution measures $\bar{R}$ and $\bar{Q}$, respectively, they are plotted against each other. As all data sets show the same behavior only the plots for the PLUS-Las-P data sets are depicted exemplary in figure 5. For $\bar{R}$, shown in figure 5(a), a trend is noticeable: with an increasing number of minutiae points $\bar{R}$ decreases, meaning the points start to cluster. Figure 5(b) shows that there is no obvious correlation between $\bar{Q}$ and the amount of minutiae. Combining the insights gained by the coherences in figure 2 and 4 we know that the recognition performance tends to be high when an optimum number of minutiae points is available and $\bar{Q}$ is low. Using this information in combination with the results in plot 5(b) may help to identify settings which produce "high quality" minutiae set on which a high recognition accuracy can be achieved.

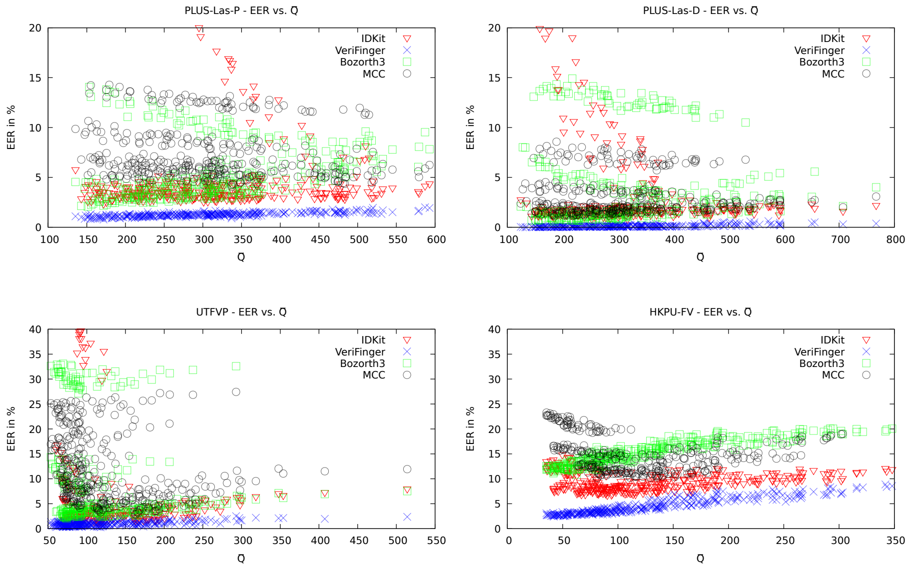
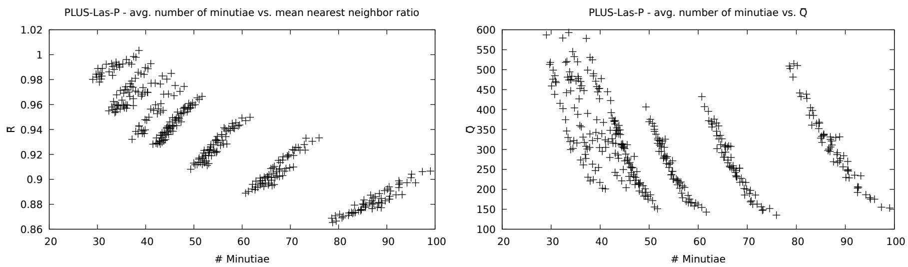


Fig. 4: EER vs. $\bar{Q}$.



(a) (b)

Fig. 5: Average number of minutiae points per sample vs. $\bar{R}$ (a) and $\bar{Q}$ (b).

5 Conclusion

In this work the influence of the number of finger vein minutiae points and their spatial distribution on the recognition accuracy was investigated. The results showed that there are correlations between recognition accuracy, minutiae number and minutiae distribution. Based on the discussion of the results for a possible usage of the proposed methods to estimate the quality of vein minutiae sets, the outcome of this work motivates further investigation on the proposed measures or a combination of them to derive a suitable measure for estimating the quality of vein samples and/or vein minutiae sets regarding minutia-based recognition techniques.

6 Acknowledgment

This project was partly funded by the Austrian Science Fund FWF project “Advanced Methods and Applications for Fingervein Recognition” under grant No. P 32201-NBL.

References

[Bo04] Bolle, R. M.; Connell, J.; Pankanti, S.; Ratha, N. K.; Senior, A. W.: Guide to Biometrics. Springer New York, 1 edition, 2004.

[CFM10] Cappelli, R.; Ferrara, M.; Maltoni, D.: Minutia Cylinder-Code: A New Representation and Matching Technique for Fingerprint Recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 32(12):2128–2141, Dec 2010.

[CFM11] Cappelli, R.; Ferrara, M.; Maltoni, D.: Fingerprint Indexing Based on Minutia Cylinder-Code. IEEE Transactions on Pattern Analysis and Machine Intelligence, 33(5):1051–1057, 2011.

[Di14] Diggle, Peter J: Statistical analysis of spatial and spatio-temporal point patterns. CRC press, 3rd edition, 2014.

[FMC12] Ferrara, M.; Maltoni, D.; Cappelli, R.: Noninvertible Minutia Cylinder-Code Representation. IEEE Transactions on Information Forensics and Security, 7(6):1727–1737, 2012.

[FMC14] Ferrara, M.; Maltoni, D.; Cappelli, R.: A two-factor protection scheme for MCC fingerprint templates. In: 2014 International Conference of the Biometrics Special Interest Group (BIOSIG). pp. 1–8, 2014.

[JY06] Jiansheng Chen; Yiu-Sang Moon: A Statistical Study on the Fingerprint Minutiae Distribution. In: 2006 IEEE International Conference on Acoustics Speech and Signal Processing Proceedings. volume 2, pp. II–II, 2006.

[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: Proceedings of the International Conference of the Biometrics Special Interest Group (BIOSIG’18). Darmstadt, Germany, pp. 1–8, 2018.

[KZ12] Kumar, A.; Zhou, Y.: Human Identification Using Finger Images. IEEE Transactions on Image Processing, 21(4):2228–2244, April 2012.

[LU21] Linortner, Michael; Uhl, Andreas: Towards Match-on-Card Finger Vein Recognition. In: Proceedings of the 2021 ACM Workshop on Information Hiding and Multimedia Security. IH&MMSec ’21, Association for Computing Machinery, New York, NY, USA, pp. 87–92, 2021.

[OU10] O’Sullivan, David; Unwin, David: Geographic information analysis. John Wiley & Sons, 2nd edition, 2010.

[PPJ01] Pankanti, S.; Prabhakar, S.; Jain, A.K.: On the individuality fingerprints. In: Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001. volume 1, pp. I–I, 2001.

[Sc79] Sclove, Stanley L.: The Occurrence of Fingerprint Characteristics as a Two-Dimensional Process. Journal of the American Statistical Association, 74(367):588–595, 1979.

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