A. Brömme, C. Busch, A. Dantcheva, C. Rathgeb and A. Uhl (Eds.): BIOSIG 2017,
Lecture Notes in Informatics (LNI), Gesellschaft fur Informatik, Bonn 2017

Intrinsic Limitations of Fingerprint Orientation Estimation

Patrick Schuch[1], Simon-Daniel Schulz[2], Christoph Busch[3]

Abstract: Estimation of orientation field is a crucial issue when processing fingerprint samples. Many subsequent fingerprint processing steps depend on reliable and accurate estimations. Algorithms for such estimations are usually evaluated against ground truth data. As true ground truth is usually not available, human experts need to mark-up ground truth manually. However, the accuracy and the reliability of such mark-ups for orientation fields have not been investigated yet. Mark-ups produced by six humans allowed insights into both aspects. A Root Mean Squared Error of about 7° against true ground truth can be achieved. Reproducibility between two mark-ups of a single dactyloscopic expert is at the same precision. We concluded that the accuracy of human experts is competitive to the best algorithms evaluated at FVC-ongoing.

Keywords: fingerprint recognition, orientation field estimation, accuracy, reproducibility

1 Introduction and Motivation

The Orientation Field (OF) of a fingerprint is a characteristic feature. It represents the local orientation of the papillary ridges on the fingerprint. The OFs form typical patterns (see figure 1). They are decisive for the orientation of the characteristic points of the fingerprint ridges: the minutiae. Minutiae are the most common biometric features when recognizing fingerprints. Further processing steps may use information of the OF, e.g. image enhancement and automated minutiae extraction. Thus, fingerprint Orientation Estimation (FOE) needs to be *accurate* to allow a precise processing. This makes FOE one of the most important sub-processes in biometric feature extraction from fingerprints [Ma09].

But what does it mean to have an *accurate* FOE? An accurate FOE shall not deviate significantly from the so-called *true ground truth* (GT), i.e. the actual OF. Thus one needs to know GT for a quantitative assessment of an FOE. Unfortunately, the true GT is usually unknown as one does not know the exact OF. To circumvent this lack of true GT, human experts may mark-up GT, i.e. estimate the OF manually and record the estimation.

Whenever estimations are made, they should be questioned and analyzed for their accuracy. If in addition humans perform the estimations, reproducibility and whether the humans need expertise can be a critical issue. Despite the fact that FOE is a key aspect in biometric feature extraction, neither accuracy nor reproducibility have been assessed in literature yet. This paper addresses both aspects of FOE by humans.

As a special use case we inspect the benchmark framework FVC-ongoing. It provides the one and only relevant benchmark for quantitative assessment of algorithms for FOE. This of course makes use of a human mark-up of the GT [CMT10]. Algorithms under assessment will perform FOE on given fingerprint samples and this estimation is compared to the

[1] NTNU, NBL Norwegian Biometrics Lab, Gjøvik, NO, patrick.schuch2@ntnu.no
[2] Dermalog Identification Systems GmbH, Hamburg, DE, simon.schulz@dermalog.com
[3] NTNU, NBL Norwegian Biometrics Lab, Gjøvik, NO, christoph.busch@ntnu.no

(a) Whorl (b) Arch (c) Right Loop (d) Right Loop

Fig. 1: The presence or absence of singularities significantly shapes the orientations fields and builds typical patterns. Those singularities are *cores* (yellow crosses) and *deltas* (red crosses). The green lines emphasize the flow of the ridges around those singularities. The relative positions of the singularities can vary the shape significantly within a pattern type (compare figures 1c and 1d).

GT. GT consists of triplets (x, y, θ^{GT}) representing ground truth orientation θ^{GT} at pixel locations (x, y). Let $\theta^{E}(x, y)$ be the estimated orientation at location (x, y).
Then accuracy can be measured as the *Root Mean Squared Error* (RMSE) over all N sampling points provided in a sample:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\theta_i^{GT} - \theta^{E}(x_i, y_i))^2} \tag{1}$$

It is worth mentioning, that the benchmark performs evaluations on two datasets: one data set contains images of good quality (GQ) and the other one contains images of bad quality (BQ). Performance is therefore measured in two scalars: $AvgErr_{GQ}$ and $AvgErr_{BQ}$ representing the average RMSE over all samples on the single datasets. This splitting takes into account the obvious fact that FOE is a harder task on BQ samples than it is on GQ samples. Published results of FVC-ongoing confirm this assumption (see figure 2). It is surprising to observe that since the FVC-ongoing benchmark was started in 2010, the $AvgErr_{BQ}$ has improved significantly over time, while $AvgErr_{GQ}$ did not. This may be an indicator for some kind lower bound for RMSE which depends on the benchmark itself. Additionally, this benchmark gives the opportunity to compare the performance of humans against the performance of algorithms tested at the benchmark.
The rest of the paper is organized as follows: Related work is described briefly in Section 2. Section 3 describes our assessment on the accuracy of FOE. The findings of this paper are summarized in section 5.

2 Related Work

Some previous work on FOE is relevant for the method proposed in this paper. One of the mark-up tools used in this work was presented by Cappelli et al. [CMM09]. Lodrova et al. have proposed averaging of minutia directions for estimations form multiple experts and define thresholds when consensus on estimations is found [Lo09]. Dactyloscopic examiners were assessed on several aspects: determination of quality [Ul14][OBB15], minutia mark-up [Ul15][Ul16], and identification decisions [Ul11][Ul12]. Oehlmann et al compared algorithms for FOE with two further measures: average deviation (as an alternative to RMSE) and percentage of area with a deviation larger than 15° [OHG15]. This bound of 15° can be considered as a threshold between a reasonable estimation and an unacceptable deviation. They proposed to use RMSE as a measure for the accuracy for FOE against GT mark-up by a human expert. Chapman et al. provided a guide for the markup of directions of minutiae [Ch13]. Capelli et al., and Turroni et al. constituted the base for the FOE benchmark at FVC-ongoing [CMT10][Tu11]. The works of Feng et al. and of Gottschlich et al. are examples, where manually marked-up OFs were used for assessment of proposed approaches [FZJ13][GMM09]. Zhao et Jain used manual markups to separate overlapping fingerprints [ZJ12].

3 Assessment

Tools We used two different tools for mark-up. Both differ in the way the mark-up is done and how the OF is constructed from the mark-up.

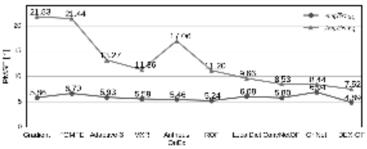


Fig. 2: Algorithms are ordered by their publication date. While $\text{AvgErr}_{\text{BQ}}$ has been improved significantly over time, $\text{AvgErr}_{\text{GQ}}$ stagnates at about 5°.

Tool A is called *FingerprintAnalyzer* (see figure 3a). It was kindly provided to us by the Università di Bologna. It was the same tool which was used for marking-up the GT at FVC-ongoing. The tool allows a markup at an equidistant grid. It supports the editor by giving an initial estimation for the OF at a selected mark-up point. If the editor does not agree with this estimation, the local OF can be corrected manually. The final OF is calculated as a interpolation based on the marked-up support points. Relevant support points for interpolation are the corner of surrounding triangles of a Delaunay triangulation on the support points. The output is the OF sampled at an equidistant grid of every eighth pixel.
Tool B was an internal tool from our team (see figure 3b). It allows to mark-up at any point of the sample. In addition to local estimations, this tool allows to mark-up singularities (compare to figure 1). The OF is calculated as a thin plate spline (TPS) on the a complex plane based on the singularities. The global shape of the OF is modeled using a Zero-Pole Model. Local deviations from this model can be corrected using control points which use a TPS to interpolate the residual. No initial orientation proposal is provided for the control points, i.e. the orientation of the control points must be set manually. The output is an interpolated OF for every pixel.

Data Acquisition Three experts with perennial experience in the domain of fingerprints and three laymen marked-up a total of 15 samples. More reliable results would require more humans involved in the time-consuming mark-up. As we were interested in the highest achievable accuracy and best reproducibility, we focused on GQ samples. There were ten GQ fingerprint samples of dataset FOE-TEST provided by FVC-ongoing (file names are *110-119*). GT marked-up by a human was available for these ten samples.
In addition, three synthetic fingerprint samples were generated by an external synthesizer tool called SFinGe [CMM04] (see figures 3f - 3g). Two pure synthetic samples completed

(a) Tool A (b) Tool B (c) SFinGe1 (d) SFinGe2 (e) SFinGe3 (f) Lines (g) Circles

Fig. 3: Two tools are used for mark-up of OF. Tool A interpolates the OF based on marked support points (yellow lines in 3a). Additionally to local orientation (green lines), our internal tool B takes into account singularities (cyan triangles and crosses in 3b) and uses Thin Plate Splines for estimation of the OF. The set of samples to be marked-up consists of the ten GQ samples of FOE-TEST, three samples generated with SFinGE (3c-3e), and two analytical patterns (3f and 3g).

the dataset to be marked-up: straight lines and circle patterns (see figures 3f and 3g). Used frequencies were similar to those in fingerprints. For these cases true GT is available.
Both mark-up tools described in section 3 were used for mark-up (see subsection 3). Mark-up was repeated in three sessions. At least one day break was made between two consecutive sessions.
In addition, one expert performed two mark-up sessions on the 50 BQ fingerprint samples of FOE-TEST. For these samples manual marked-up GT was available, too.
Dataset FOE-TEST provided GT subsampled at an equidistant grid at every eighth pixel. This sampling rate was the lowest common denominator and was therefore used for all comparisons. In addition, the foreground area containing the fingerprint is provided with the set. As only these areas were relevant, only those were evaluated in the RMSE.

4 Analysis and Results

Accuracy The accuracy of mark-ups for FOE can be assessed most accurately only in comparison to unbiased true GT. We therefore inspected the RMSE achieved on the synthetic SFinGe samples, the lines sample and the circles sample (see figure 3). Table 1 revealed that experts performed significantly better than laymen on the task of FOE. They achieved RMSE of 7.8° for all SFinGe samples when the tool A was used. When tool B was use, 7.2° was achieved. These performances was better than the RMSE of 9.3° and 11.9° respectively achieved by the laymen. Expertise in the domain of fingerprint recognition was therefore necessary to produce a more reliable mark-up.

Person	Session	SFinGe 1	SFinGe 2	SFinGe 3	Lines	Circles	μ_{SFinGe}
Expert 1	1	8.9/7.7	8.9/8.3	6.7/5.6	1.6/0.7	6.1/2.7	**8.2/7.2**
	2	8.9/7.3	8.3/8.2	6.5/7.1	2.1/0.7	6.2/0.9	**7.9/7.5**
	3	7.7/5.3	6.9/7.9	5.2/5.7	1.7/0.7	6.7/0.7	**6.6/6.3**
Expert 2	1	8.5/6.8	8.8/7.4	8.7/6.1	1.7/0.7	8.3/1.3	**8.7/6.8**
	2	7.8/6.9	7.8/8.2	7.2/5.4	1.3/0.7	6.9/0.6	**7.6/6.9**
	3	8.5/6.1	9.0/7.8	8.6/5.9	3.4/0.7	6.6/0.6	**8.7/6.6**
Expert 3	1	9.4/9.2	10.0/7.4	6.6/6.3	2.4/0.7	5.1/0.8	**8.6/7.6**
	2	8.3/9.5	8.6/8.5	5.6/6.5	2.6/0.7	2.9/0.7	**7.5/8.2**
	3	8.3/9.6	6.6/8.7	4.7/5.9	1.5/0.7	2.2/1.1	**6.5/8.0**
Layman 1	1	12.3/21.4	9.7/13.8	7.8/19.8	2.2/0.7	4.8/6.3	**9.9/18.3**
	2	17.0/23.6	9.4/13.2	7.9/11.8	2.5/0.7	8.4/6.8	**11.5/16.2**
	3	11.7/13.0	10.8/13.5	9.5/8.0	1.9/0.7	8.1/8.7	**10.7/11.5**
Layman 2	1	10.7/11.3	7.5/12.4	7.6/8.3	1.5/2.8	5.0/7.3	**8.6/10.7**
	2	9.5/11.5	8.2/13.4	5.2/6.5	2.0/3.5	5.4/6.5	**7.6/10.5**
	3	10.8/14.7	8.2/11.2	8.3/8.4	2.5/0.0	5.4/6.6	**9.1/11.4**
Layman 3	1	10.1/9.4	9.8/10.4	5.8/8.7	1.9/2.1	7.6/5.9	**8.6/9.5**
	2	8.2/8.5	9.0/9.5	7.8/6.6	4.4/0.3	5.6/3.9	**8.3/8.2**
	3	10.6/10.8	8.5/11.1	7.9/9.1	2.6/2.8	5.6/2.6	**9.0/10.4**
$\mu_{Experts}$	**all**	**8.5/7.6**	**8.3/8.0**	**6.6/6.1**	**2.0/0.7**	**5.7/1.1**	**7.8/7.2**
$\mu_{Laymans}$	**all**	**11.2/13.8**	**9.0/12.1**	**7.5/9.7**	**2.4/1.5**	**6.2/6.1**	**9.3/11.9**
μ_{All}	**all**	**9.8/10.7**	**8.7/10.0**	**7.1/7.9**	**2.2/1.1**	**5.9/3.6**	**8.5/9.5**

Tab. 1: RMSE when marking-up with Tool A/B

The best single mark-up session for all SFinGe samples achieved RMSE of 6.2°. The RMSE achieved for the lines sample showed that this task can be performed with high accuracy. Tool B could be used to better approximate the circles due to the capability to mark-up cores.

Gaining Expertise The development of the RMSE over the consecutive sessions gave insight, whether FOE is a task which could be learned fast. Surprisingly, laymen did not improve constantly over time. Despite this, the RMSE for the experts tended to improve over time. We assumed this effect did not reflect an improvement in the task of FOE itself. It reflected the fact that the experts got used to the tools and thus became able to express their knowledge of OF better with the tools.

Humans vs Algorithms Table 2 contains the RMSE achieved against the GT provided for the samples of FOE-TEST. This allowed to compare the performance of humans against the capabilities of those algorithms evaluated at FVC-ongoing. The mean RMSE $\mu_{110-119}$ for all experts achieved with the tool A is 6.2° and 7.0° for the tool B respectively. It is worth mentioning, that this was opposite to the higher accuracy against the true GT from the synthetic images when using tool B. This was likely due to the fact, that tool A was used to mark-up the GT. Thus, the results might slightly be biased by the mark-up tool. The best RMSE over all samples $\mu_{110-119}$ was achieved by expert 3 with the tool A: 5.2°. This was competitive to the best algorithm at FVC-ongoing (see figure 2).
As lower bounds for BQ samples were of interest, too, we performed some extra assessments. One expert additionally performed two mark-up sessions on the 50 bad quality images of dataset FOE-TEST. The expert achieved a RMSEs of 8.4° in the first and 8.3° in the second session against the alleged GT when using tool B and 11.0° and 9.6° with tool A respectively. The tool B might therefore be more appropriate for mark up of bad quality images. However, this accuracy was competitive to the best algorithm at FVC-ongoing which is called *DEX-OF* [SSBng].

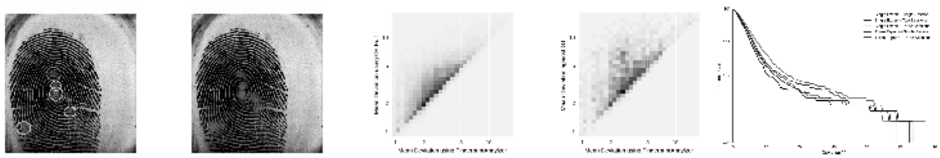
Person	Session	110	111	112	113	114	115	116	117	118	119	$\mu_{110-119}$
	1	7.6/7.3	4.9/6.2	5.5/6.1	7.7/7.0	7.3/7.4	5.3/7.0	5.9/6.3	5.5/6.6	7.6/6.8	5.2/6.3	**6.2/6.7**
Expert 1	2	6.6/5.7	6.7/6.4	6.5/5.8	7.9/7.0	8.3/6.5	5.0/6.4	7.4/5.4	5.9/7.4	7.0/7.0	5.1/5.2	**6.7/6.3**
	3	5.0/4.9	4.5/5.7	5.3/6.1	7.2/7.0	7.8/7.1	5.0/6.3	5.5/5.1	5.1/6.5	6.4/7.2	4.3/5.7	**5.6/6.2**
	1	6.8/6.7	5.8/6.1	7.4/9.5	9.9/7.3	8.7/9.5	4.8/7.9	6.1/5.5	5.5/8.9	6.4/7.9	5.3/5.3	**6.6/7.5**
Expert 2	2	6.9/5.3	4.9/6.6	5.7/9.2	8.0/6.8	7.6/8.5	4.3/6.5	5.6/6.1	5.4/7.9	6.7/8.1	5.0/5.1	**6.0/7.0**
	3	6.6/6.5	6.6/5.9	6.8/10.3	8.7/9.2	7.9/10.1	4.8/6.8	6.3/5.4	6.1/7.5	5.9/7.9	7.4/6.2	**6.7/7.6**
	1	6.4/6.5	6.4/6.9	6.4/7.7	8.5/8.5	8.1/10.3	6.6/6.7	6.3/8.4	8.6/8.7	6.7/8.1	6.2/6.1	**7.0/7.8**
Expert 3	2	5.1/7.0	4.6/7.7	4.8/6.1	6.3/8.9	6.6/7.7	4.2/5.5	5.4/6.7	7.1/8.6	5.5/8.9	4.4/5.7	**5.4/7.3**
	3	4.9/7.4	4.5/6.0	4.5/6.1	5.8/7.7	6.7/8.7	4.9/6.0	5.4/6.6	4.4/8.2	6.3/7.4	4.8/5.7	**5.2/7.0**
$\mu_{Experts}$	**all**	**6.2/6.4**	**5.4/6.4**	**5.9/7.5**	**7.8/7.7**	**7.7/8.4**	**5.0/6.6**	**6.0/6.2**	**6.0/7.8**	**6.5/7.7**	**5.3/5.7**	6.2/7.0

Tab. 2: RMSE against the alleged ground truth provided in dataset FOE-TEST (file names *110-119*) when marking-up with tool A/tool B. The lowest RMSE achieved over all session is 5.2°.

Local Deviations The distribution of deviations was not uniform for every sampling point. Figures 4a and 4b visualize the degree of dissent on local orientations for all experts on a single sample. Let $\theta_i^E(x,y)$ be the local estimation at location (x,y) from mark-up i. Then the local dissent $\delta(x,y)$ can be measured as the mean deviation from an averaged estimation $\mu_\theta(x,y)$ over M mark-ups:

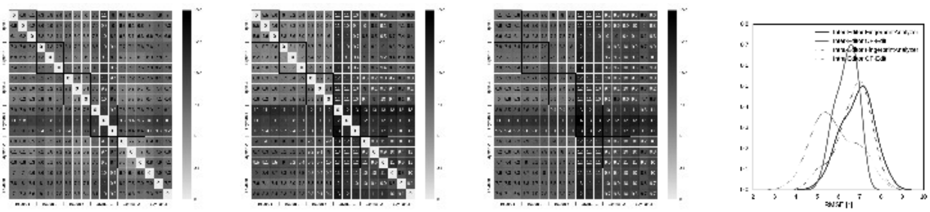
$$\mu_\theta(x,y) = 0.5 * \arctan\left(\frac{\sum_{i=1}^{M}\sin(2\cdot\theta_i^E(x,y))}{\sum_{i=1}^{M}\cos(2\cdot\theta_i^E(x,y))}\right) \tag{2}$$

$$\delta(x,y) = \frac{1}{M}\sum_{i=1}^{M}\left|\measuredangle(\theta_i^E(x,y), \mu_\theta(x,y))\right| \tag{3}$$



(a) Tool A (b) Tool B (c) Between Tools (d) Against GT (e) Averaging Mark-ups

Fig. 4: The local dissent among experts on FOE (red tinting in figures 4a and 4b) is similar for both tools. Dissent is strong near singularities (yellow circles), saddle points of curvature (blue rectangle), and where the experts need to choose between local fidelity and smoothness (green circle). Where dissent is large among the expert, the deviation to true GT is large, too (4d). Averaging over more than one mark-up can reduce such deviations (4e).



(a) Tool A (b) Tool B (c) Between Tools (d) KDE of RMSE

Fig. 5: RMSE between all sessions of all experts and laymen. The block diagonal matrix is highlighted by black squares. Those contain the comparison between all sessions of a single person and therefore allow inference on reproducibility of mark-ups.

The more intense a block was colored red, the larger was the dissent. Not surprisingly, the dissent was larger in the vicinity of singularities than it was in regions of low curvature. The local distribution of dissent was similar for both tools (see figure 4c). The area of dissent near singularities was larger for tool B than it was for tool A (yellow circles). Due to the fact that singularities could be marked-up with tool B, slight deviations in position of singularities led to larger areas of dissent. Relevant deviations can also be found where curvature has saddle points, i.e. where the ridges change their bending (blue rectangle). Additionally, there were deviations at those points, where experts had to decide between smoothness of the OF and high fidelity to local changes of the OF (green circle). This was more an individual bias than it was a critical deviation.
The local deviation among the experts from their estimated mean was strongly correlated to their mean deviation against the GT on the three samples generated with SFinGE. Pearson's correlation coefficient between both mean deviations is 0.8. Therefore, it is likely that dissent among multiple mark-ups will coincide with deviations from true GT.

Reproducibility Whenever humans are involved in processes, reproducibility is an important issue . Single mark-up sessions of the human editors were compared against each other to assess this aspect. Figures 5a-5c visualizes the RMSE between all mark-ups made by the six human editors. Since also RMSE between all sessions of a single person were

included in this graphic, it contains information regarding reproducibility. In general, experts achieved lower RMSE between their sessions than the laymen did. This holds except for layman 2 when marking up with tool A. This good reproducibility needed to be put into perspective of significant higher deviation against true GT (see table 1).
However experts could achieve RMSE between 5° and 7° between two mark-ups. Surprisingly, these accuracies were only slightly better than the accuracies between the particular experts. This was an indicator that the single mark-ups were good estimations of the true OF. The RMSE between the two sessions on the BQ samples was 11.7° when using the tool A and 7.6° when using the tool B.

Approximating True GT It seemed, that the mark-ups could be interpreted as true GT disturbed by some *noise*. If the noise is mean-free, averaging mark-ups will reduce the influence of noise. Figure 4e visualized the empirical cumulative density function of deviations between μ_θ and the true GT of the SFinGe samples. The more mark-ups involved in averaging, the lower was the deviation against the true GT. There was no significant difference between averaging all three mark-ups of one expert and averaging one session each from all three experts.

5 Conclusions

By extensive and time consuming mark-up of OFs, we investigated questions regarding FOE when performed by humans. We found that expertise in fingerprints increases the accuracy of marked-up OFs. Experts achieved an RMSE of about 7° compared to true GT. Averaging over more than one mark-up increased the accuracy. Inspection of multiple mark-ups of a single expert showed, that mark-ups could be produced at similar values of RMSE. These values were, therefore, interpreted as rough lower bounds for a reasonable accuracy at FVC-ongoing. When humans were compared to the alleged GT at benchmark FVC-ongoing, they achieved roughly 5° on GQ samples and about 8.4° on BG samples respectively. This was competitive to the best algorithms evaluated by FVC-ongoing.

Acknowledgment

The authors would like to thank the team from Università di Bologna for providing us with their mark-up tool. Additionally, we would like to thank all experts and laymen involved in the mark-up of the OFs.

References

[Ch13] Chapman, Will; Hicklin, RA; Kiebuzinski, GI; Komarinski, Peter; Mayer-Splain, John; Taylor, Melissa; Wallner, Rachel: Markup Instructions for Extended Friction Ridge Features. NIST Special Publication, 1151, 2013.

[CMM04] Cappelli, Raffaele; Maio, D; Maltoni, D: SFinGe: an approach to synthetic fingerprint generation. In: International Workshop on Biometric Technologies (BT2004). pp. 147–154, 2004.

[CMM09] Cappelli, Raffaele; Maio, Dario; Maltoni, Davide: Semi-automatic enhancement of very low quality fingerprints. In: Image and Signal Processing and Analysis, 2009. ISPA 2009. Proceedings of 6th International Symposium on. IEEE, pp. 678–683, 2009.

[CMT10] Cappelli, Raffaele; Maltoni, Davide; Turroni, Francesco: Benchmarking local orientation extraction in fingerprint recognition. In: Pattern Recognition (ICPR), 2010 20th International Conference on. IEEE, pp. 1144–1147, 2010.

[FZJ13] Feng, Jianjiang; Zhou, Jie; Jain, Anil K: Orientation field estimation for latent fingerprint enhancement. IEEE transactions on pattern analysis and machine intelligence, 35(4):925–940, 2013.

[GMM09] Gottschlich, Carsten; Mihailescu, Preda; Munk, Axel: Robust orientation field estimation and extrapolation using semilocal line sensors. IEEE Transactions on Information Forensics and Security, 4(4):802–811, 2009.

[Lo09] Lodrova, Dana; Busch, Christoph; Tabassi, Elham; Krodel, Wolfgang; Drahansky, Martin et al.: Semantic conformance testing methodology for finger minutiae data. Proceedings of the Special Interest Group on Biometrics and Electronic Signatures (BIOSIG), pp. 31–42, 2009.

[Ma09] Maltoni, Davide; Maio, Dario; Jain, Anil K; Prabhakar, Salil: Handbook of fingerprint recognition. springer, 2009.

[OBB15] Olsen, Martin Aastrup; Bockeler, Martin; Busch, Christoph: Predicting dactyloscopic examiner fingerprint image quality assessments. In: Biometrics Special Interest Group (BIOSIG), 2015 International Conference of the. IEEE, pp. 1–12, 2015.

[OHG15] Oehlmann, Lars; Huckemann, Stephan; Gottschlich, Carsten: Performance evaluation of fingerprint orientation field reconstruction methods. In: Biometrics and Forensics (IWBF), 2015 International Workshop on. IEEE, pp. 1–6, 2015.

[SSBng] Schuch, Patrick; Schulz, Simon-Daniel; Busch, Christoph: Deep Expectation for Estimation of Fingerprint Orientation Fields. forthcoming.

[Tu11] Turroni, Francesco; Maltoni, Davide; Cappelli, Raffaele; Maio, Dario: Improving fingerprint orientation extraction. Information Forensics and Security, IEEE Transactions on, 6(3):1002–1013, 2011.

[Ul11] Ulery, Bradford T; Hicklin, R Austin; Buscaglia, JoAnn; Roberts, Maria Antonia: Accuracy and reliability of forensic latent fingerprint decisions. Proceedings of the National Academy of Sciences, 108(19):7733–7738, 2011.

[Ul12] Ulery, Bradford T; Hicklin, R Austin; Buscaglia, JoAnn; Roberts, Maria Antonia: Repeatability and reproducibility of decisions by latent fingerprint examiners. PloS one, 7(3):e32800, 2012.

[Ul14] Ulery, Bradford T; Hicklin, R Austin; Roberts, Maria Antonia; Buscaglia, JoAnn: Measuring what latent fingerprint examiners consider sufficient information for individualization determinations. PloS one, 9(11):e110179, 2014.

[Ul15] Ulery, Bradford T; Hicklin, R Austin; Roberts, Maria Antonia; Buscaglia, JoAnn: Changes in latent fingerprint examinersâ markup between analysis and comparison. Forensic science international, 247:54–61, 2015.

[Ul16] Ulery, Bradford T; Hicklin, R Austin; Roberts, Maria Antonia; Buscaglia, JoAnn: Interexaminer variation of minutia markup on latent fingerprints. Forensic science international, 264:89–99, 2016.

[ZJ12] Zhao, Qijun; Jain, Anil K: Model based separation of overlapping latent fingerprints. IEEE Transactions on Information Forensics and Security, 7(3):904–918, 2012.