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Fingermark Quality Assessment: An Open-Source Toolbox

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Abstract: Fingermark quality assessment is an important step in a forensic fingerprint identification process. Often done in the scope of criminal investigation, it is performed by trained fingerprint examiners whose quality assessment can be rather subjective. The goal of this work is to develop an automated fingermark quality assessment tool, which would assist the fingermark examiners in their work. In this paper, we present a fast, open-source, and well documented fingermark quality assessment toolbox, which contains more than 20 algorithms for feature extraction, segmentation, and enhancement of fingermark images. We demonstrate the utility of the toolbox by assembling a feature vector and training various baseline machine learning models, capable of predicting the quality of fingermark images with high accuracy. The AFQA toolbox source code is publicly available online.

Keywords: fingermark, forensic, biometric, quality, evaluation, open-source.

1 Introduction

Fingerprint comparison is one of the oldest types of biometric identification, used extensively in automated fingerprint identification systems (AFIS) for forensic investigations. A particular challenge in this area present fingermarks (in the USA latent fingerprints), partial friction ridge skin impressions typically from fingertips, left in an unconstrained environment, e.g., a crime scene. Fingermarks are lifted from various surfaces and their quality is influenced by several external factors, which often result in distorted or only partially visible impressions. The scientific method of comparing fingermarks, ACE-V [As99], is well established and followed by trained forensic examiners. An important first step in this process is determining the quality (or value for identification) of a fingermark. This value establishes how the fingermark will be processed and indicates, whether its quality is sufficient for finding a mated fingerprint in an open-set biometric dataset. Due to the involvement of human experts, quality assessment is subjective, prone to bias and can potentially result in evidence mishandling. An Automated Fingermark Quality Assessment (AFQA) toolbox assists forensic fingermark examiners by proposing a probabilistic quality value, helps to reduce their subjectivity and improves their efficiency.

Based on the initial review, a novel automated, reliable, and open-source AFQA implementation would greatly benefit the forensic community. Within the existing work, accessibility and reproducibility are currently the major limiting factors: (i) Commercially available solutions are widespread but require the user to pay for the product. In rare cases,

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companies offer limited access to their software, but only for research purposes and such arrangements do not include access to the source-code. (ii) Some solutions are designed specifically for local law enforcement or larger intelligence agencies and are not available publicly to minimize intentional tampering or spoofing with the goal of concealing identity. (iii) Existing published work is rarely accompanied with open-source code, data, or data annotations. This is particularly noticeable in novel approaches, which are largely data-driven machine learning (ML) solutions [Yo13, Ch18]. Popular fingermark datasets being recently discontinued [GM00], it makes many methods difficult or in some cases impossible to reproduce. (iv) Some fingerprint-related algorithms, published in the open-source format [TWW04, Ta21], are commonly implemented in low-level programming languages and intended for integration into end products. While this is beneficial in a production environment, research productivity is lowered. Furthermore, the majority of available open-source programs are focused on fingerprints and not on fingermark processing.

To boost research in this field and improve accessibility of related methods, we propose an open-source AFQA toolbox for fingermark analysis and quality assessment. This includes a centralized and ready to use collection of most frequently used computer vision techniques for feature extraction, segmentation, and enhancement of friction ridge images, written in a high-level programming language (*Python*). We use the toolbox to extract features from fingermarks and construct a fixed-length feature vector. Using popular ML algorithms and with the help of existing quality assessment methods to annotate the data, we train predictive models in order to assess the quality of fingermarks. We demonstrate the accuracy of our models on a publicly available fingermark dataset and provide the motivation in favour of using the AFQA toolbox to develop new quality assessment methods.

In Section 2, we describe the related work within friction ridge quality assessment. In Section 3, we present and describe the fingermark toolbox and demonstrate its usage by proposing a quality assessment pipeline in Section 4. Finally, we compare our approaches, discuss the results in Section 5, and conclude with final thoughts in Section 6.

2 Related work

Fingerprint quality. Initially, quality assessment of fingerprints was based on various local image quality indicators, such as local frequency and clarity, deviation of Gabor features, and other pixel intensity or gradient methods [Al07]. The National Institute of Standards and Technology (NIST) fist aimed to standardize fingerprint quality assessment and developed the NIST Fingerprint Image Quality (NFIQ) algorithm [TWW04]. This was the first attempt to define a fingerprint quality measure as being indicative of the probability to find a mated reference fingerprint in a database for a questioned fingerprint. Thanks to the advances in fingerprint recognition technology, NIST initiated work on an upgrade, the NFIQ 2 [Ta21]. The authors implemented 155 feature extraction algorithms, eliminated features with low predictive power and trained an improved random forest classifier to assign quality values. They observed improved predictive capabilities and a faster execution time in comparison with the original NFIQ. The open-source method was gradually improved and culminated with a recent (2021) release of version NFIQ 2.1.

Fingermark quality. After the 2004 Madrid bombings, the FBI misidentified a prime suspect based on a single fingermark. In response, they investigated the decision-making process of their forensic examiners. The findings were used to develop the Universal Latent Workstation (ULW), a toolbox assisting forensic examiners with fingermark analysis, which also contains a fingermark quality metric (LQmetric). The LQmetric is not publicly available and is only partially published [KBH20]. Based on operational feedback from the FBI Laboratory, it performs well on good- and bad-quality fingermarks, but not on borderline cases [HGB19]. To define a quality measure specifically for fingermarks, Yoon *et al.* developed the Latent Fingerprint Image Quality (LFIQ) [Yo13]. The algorithm uses a combination of local clarity indicators and minutiae data to determine quality. The method relies on manual minutiae extraction for best performance. Sankaran *et al.* [SVS13] proposed a heuristic to determine the local clarity and quality of fingermarks, however, they did not consider minutiae data as a qualitative indicator. Chugh *et al.* [Ch18] gathered expert crowd-sourced data and cross referenced it to develop a predictive model for quality assessment. Ezeobiejesi *et al.* [EB18] were the first to utilize deep learning in the context of quality assessment, however, in their approach, the final quality measure is computed trivially only by counting the number of patches of certain quality. In general, published fingermark quality assessment methods use a combination of commonly used algorithms, heuristics, and machine learning practices for processing friction ridge impressions, which we combined into a versatile open-source collection.

3 Automatic Fingermark Quality Assessment Toolbox

In this section we describe the contents of the AFQA Toolbox. The algorithms included are presented graphically in Figure 1. The majority of algorithms (green labels) are implemented in Python and make use of common Python libraries, such as *NumPy*, *SciPy*, *scikit-learn*, *scikit-image* and *OpenCV*. For other methods, which benefit more from their original low-level implementation, we offer a Python wrapper function (red labels), which enables seamless integration of complex methods into the toolbox. The AFQA toolbox is provided ”as-is” under the MIT open-source licence and can be accessed online: `https://github.com/timoblak/OpenAFQA`.

Preprocessing. Determining the region of interest is the first step when processing a friction ridge image. The foreground, containing friction ridge information, is separated from the often noisy background. This task is particularly challenging in cases, in which fingermarks are captured directly on the surface, on which they were deposited. The friction ridge is typically described using the features distributed at different levels. The toolbox includes a heuristic algorithm, which determines the fingermark foreground based on the analysis of pixel values in a local area. The friction ridge impression can often include distorted regions, which are recoverable with the use of enhancement algorithms. Such algorithms exploit the deterministic structure of friction ridge to correct local damage and improve ridge clarity. The initial set of tools includes a Difference of Gaussian-based filter [MH80], which enhances local contrast, and Hong’s method [HWJ98], which uses oriented Gabor filters to enhance the structure.

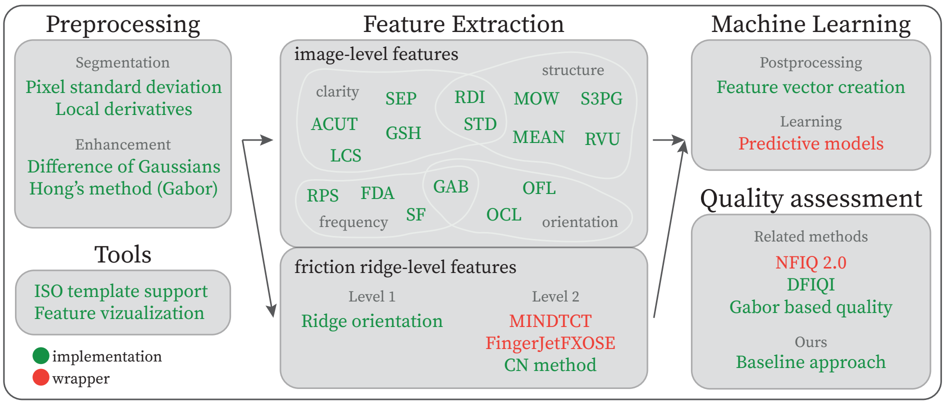


Fig. 1: **AFQA toolbox.** The toolbox (Python) contains pre-processing and feature extraction modules and includes other useful tools for friction ridge impression analysis.

Feature extraction. Friction ridge skin has inherent features, categorized into 3 levels of detail: (i) Level 1 features represent the flow of the friction ridge and its class, which is based on abrupt changes in friction ridge orientation. These features are usually detectable even in low quality or low resolution images. (ii) Level 2 details describe the salient points (endings and bifurcations) of individual ridges, called minutiae points. Many automatic fingerprint identification systems (AFIS) are heavily dependent on level 2 details. Similarly, they are used extensively in mark-to-print comparisons by forensic experts. (iii) Level 3 details are most visible on high resolution images and describe friction ridge at the highest level, e.g., skin pores, shapes of ridges, etc. Such features are highly deterministic, but can be hard to detect and compare. Due to the widespread use of level 2 features, we include in our toolbox several methods for minutiae extraction. The first is MINDTCT, an algorithm included in the NIST Biometric Image Software (NBIS)[3] distribution and used by NFIQ as well as in FBI's ULW. The second is a robust open-source minutiae extractor called FingerJetFXOSE[4], also used in the NFIQ 2. For these methods, we provide a wrapper function, which calls either a compiled binary or a library, implemented in a low-level language. Additionally, we include a simple and customizable Python implementation of the Crossing Number algorithm [Ka08].

Another class of features originates from the more general field of image quality. Through time, these were adopted specifically for analysing friction ridge impressions and are used commonly within the related literature [LJY02, CJY04, OŠB16, Sw21, Ta21]. These features can be used to capture the following friction ridge properties: (i) *Frequency* of ridges on human fingers has a known value of around 2.1 and 2.4 ridges/mm for males and females, respectively. A deviation from this value indicates the absence of friction ridge or the presence of local deformations. To calculate frequency, we use Gabor filtering of 2D Fourier transform. (ii) *Clarity* describes the separability between pixel values of nearby

[3] https://www.nist.gov/services-resources/software/nist-biometric-image-software-nbis
[4] http://github.com/FingerJetFXOSE/FingerJetFXOSE

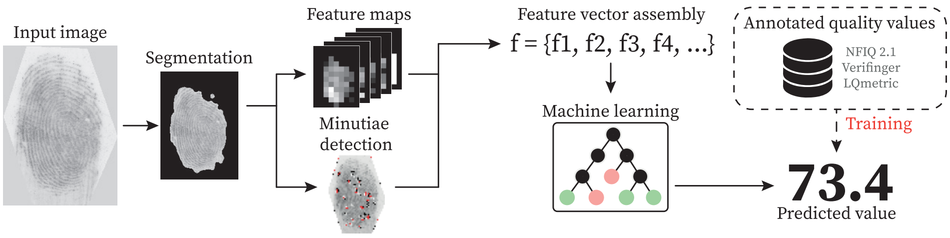


Fig. 2: **Predictive pipeline.** Predictive pipeline of AFQA toolbox, consisting of pre-processing, feature extraction, and machine learning algorithms.

ridges and valleys of the impression. Higher clarity ridges in close proximity to detected minutiae points indicate higher probability of their existence. We use image derivatives or other pixel intensity methods to calculate local clarity. (iii) *Orientation* of ridges should not change drastically in a local neighborhood of image blocks. A large difference in orientation could indicate a presence of local distortions or singular points. We calculate orientation with image gradients or by analyzing the frequency domain. (iv) *Structure* is another important factor. Ideally, the width of ridges should be consistent and comparable to the width of valleys. The ridge structure is extracted by using various pixel intensity methods.

Feature vector assembly. Due to the unconstrained nature of fingermark imposition, their image can vary drastically. To represent all fingermarks with a unified description, our toolbox enables automatic construction of a fixed-length feature vector from minutiae data and feature maps of different sizes.

4 Baseline quality assessment

In this section, we propose a baseline quality assessment method, which is derived from the AFQA toolbox feature vectors. The pipeline is visualized in Fig. 2.

For an input fingermark impression, we use image equalization and a heuristic analysis of local pixel values to determine the friction ridge area. Then, in a block-wise manner, the 15 feature extraction algorithms calculate local features, which result in 15 feature maps. FingerJetFXOSE algorithm is used to detect minutiae points within the segmented region. Each of the 15 feature maps are then compressed into a vector of 12 values. The first two values represent the mean and standard deviation of the entire feature map. The remaining 10 values represent a histogram with 10 bins, where each bin amounts to the number of values within a specific range. The edges of histogram bins are computed from an average feature map of the entire training dataset. Minutiae data are described in a similar fashion with a vector of length 12. First value represents the mean minutia quality, the second value is the number of all detected minutiae, and the remaining 10 values again represent a histogram of qualities of detected minutiae. The minutiae quality is calculated for each

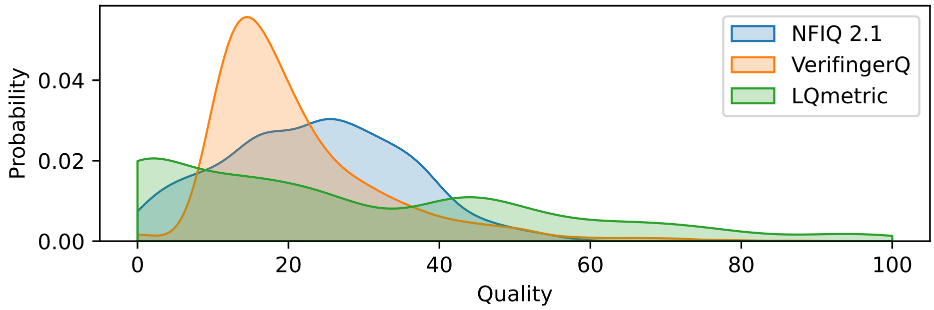


Fig. 3: **Distribution of quality scores.** Shown here are the annotated labels of the test set (NIST SD301 dataset) by three different quality assessment methods. The majority of scores is clustered towards the low quality side of the spectrum.

detected minutiae using FingerJetFXOSE. The aggregated fingermark feature vector is 192 features long.

Different ML techniques are used to train three predictive regression models for fingermark quality assessment, all of which are implemented in the *scikit-klearn* Python library. The first is a fully connected neural network, which has a single hidden layer with 100 neurons using ReLu activation and a single linear output neuron. The second is a random forest regressor, which uses an ensemble of 750 decision trees with a maximum depth of 110. The third method is a support vector regressor (SVR), for which default parameters are used. For all methods, the hyper-parameters were determined by using random search across a wide range of available values and validated on a reserved part of the training data. The task for each quality estimator is then to minimize the square difference between predicted quality values and the annotated quality values. Since dataset annotation with trained forensic examiners was not available at this point of time, we employ existing quality assessment algorithms to provide the necessary baseline quality labels for fingermark images. We use the following methods to annotate the public datasets:

- **NFIQ 2.1** [Ta21] is an open-source software, originally trained and intended for predicting quality values of flat fingerprints.
- The fingerprint quality assessment method included in the Verifinger SDK [Ne98], sold by a commercial vendor Neurotechnology. We refer to it as the **VerifingerQ** metric in this paper.
- **LQmetric** [KBH20] is fingermark quality measure, used within the FBI's Universal Latent Workstation software.

All three quality assessment methods are used to generate three sets of ground-truth labels, which are then used to train three different models for each of the ML approaches.

Tab. 1: **Evaluation results on the test set.** Random forest achieved best results in terms of performance metrics. Our feature vector is able to capture NFIQ 2.1 and VerifingerQ properties but struggles with LQmetric scores.

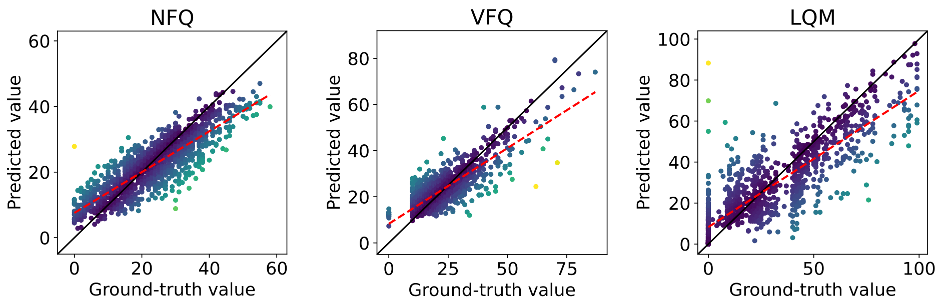
	Neural network			**Random Forest**			**SVR**		
Model	MSE	MAE	r^2	MSE	MAE	r^2	MSE	MAE	r^2
NFQ	71.63	6.09	0.50	41.62	5.16	0.71	49.84	5.51	0.65
VFQ	47.51	5.07	0.64	41.50	4.84	0.68	56.81	5.49	0.57
LQM	183.00	9.35	0.72	181.50	9.66	0.72	281.15	12.65	0.56

5 Evaluation

Experimental setup. We use NIST SD 302 [Fi18a] and SD 301 [Fi18b] fingermark image datasets. Both datasets contain fingermarks, lifted from various surfaces by trained forensic experts in a simulated environment. To better capture the properties of the whole spectrum of friction ridge quality, we use fingermark as well as fingerprint images to train the models. We split the data into a training set of 10,000 fingermarks (SD 302) and 2,000 fingerprints (SD 302), and a test dataset of 1,200 fingermarks (SD 301). The distribution of scores attributed to fingermarks by the three quality values is shown in Fig. 3. We evaluate the performance of the three trained ML models with common regression metrics. We monitor the Mean Squared Error (MSE), as well as the Mean Absolute Error (MAE) to reduce the effect of the predicted outliers. To assess the correlation between the predicted and ground-truth quality values, we also calculate the coefficient of determination r^2.

Results and comparison. By using the annotations from existing quality assessment methods NFIQ 2.1, VerifingerQ, and LQmetric, we produce three models, which we label NFQ, VFQ, and LQM, respectively. The results are shown in Table 1. Based on the metrics alone, the random forest regressor was able to approximate fingermark quality the closest for all annotated sets of scores. Neural network and SVR performed slightly worse on average. The neural network model was able to estimate VerifingerQ and LQmetric scores better while, in contrast, the SVR achieved better results on NFIQ 2.1 scores.

There are notable differences in MSE and MAE metrics between models trained on different sets of scores, particularly LQM stands out out of the three. This, however, is due to the different distribution spread of the annotated scores. A more comparable metric here is r^2, which shows the amount of variance, that can be explained by the learned model. Despite higher MAE and MSE metrics, the r^2 achieved with LQmetric scores is the highest, which means the correlation of predicted scores with original scores is higher. The high r^2 score of around 0.7 suggests that the assembled feature vector is able to capture the properties of all quality assessment algorithms, which were used to annotate the data. Overall, the VFQ model, trained using random forest, achieves the smallest MSE and MAE values. While the same metrics are slightly higher for NFQ and LQM random forest models, the coefficient of determination r^2 is higher, which indicates predicted NFIQ 2.1 and LQmetric scores are better correlated with the ground-truth values in comparison with VerifingerQ scores.

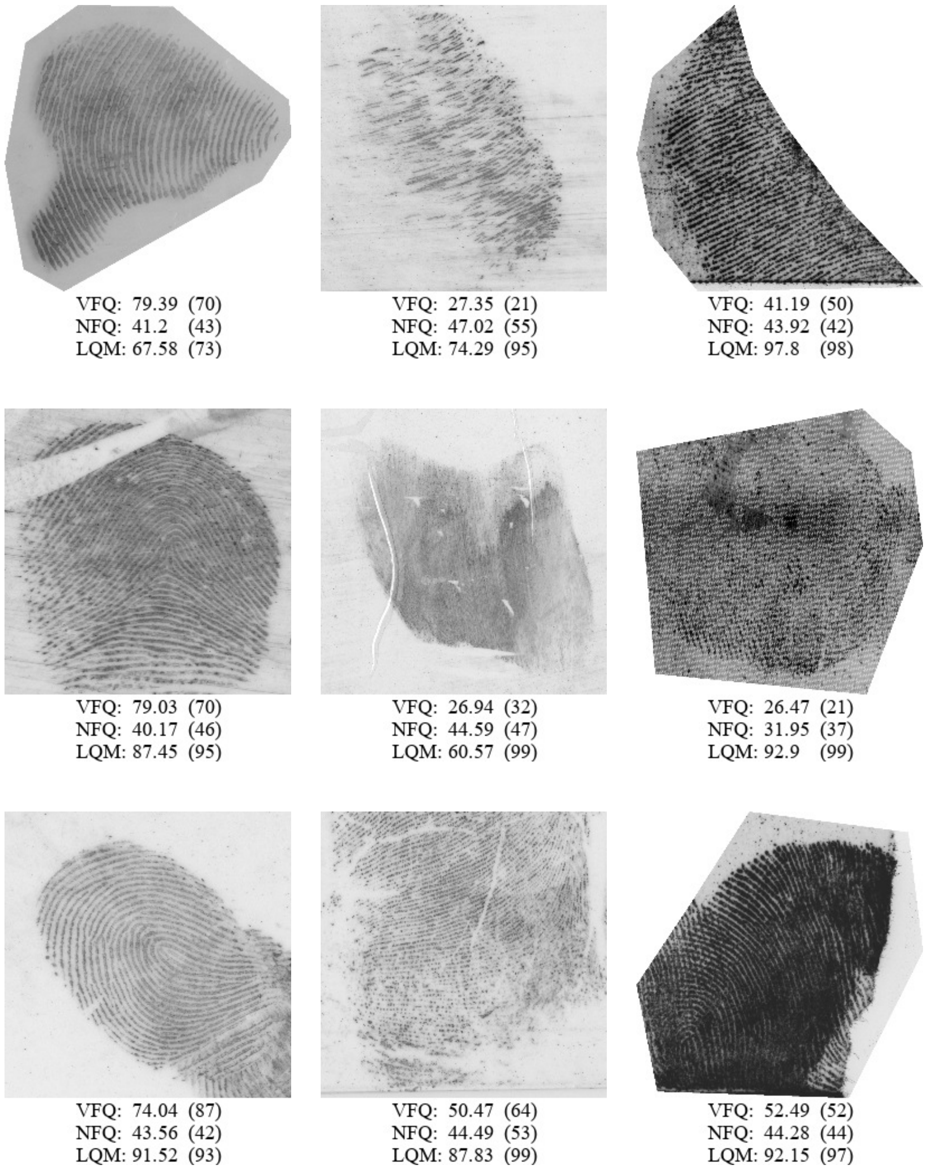


(a) (b) (c)

Fig. 4: **Random forest predictions.** The models are trained using (a) NFIQ 2.1, (b) VerifingerQ, and (c) LQmetric quality values. All models appear to slightly overestimate the lower quality fingermark values and underestimate higher quality fingermarks, as indicated by the red regression line. Lighter color indicates larger error between the prediction and ground truth values.

In Fig. 4, we show scatter plots of predicted and ground-truth quality scores for the best performing random forest regressor. The NFQ model forms the most uniform distribution with only a few outliers and shows a clear trend, following the ideal diagonal line. The VFQ model shows a similar picture with small differences. First, there is a gap with no values in the bottom left corner of the graph, which exists because 10 was the lowest score that VerifingerQ attributed to fingermark images. The exception are a few examples where the method failed and a score of 0 was assigned instead. In contrast with the NFQ, the VFQ attributes a wider range of quality values. Finally, the predictions of the LQM model are most scattered across the spectrum but still follow a clear trend. The reason again is due to the larger variance in initial annotations. The red regression line is displayed for all models and shows that all models tend to slightly overestimate bad quality fingermarks and underestimate good quality fingermarks. Around the area, where the regression line crosses the ideal diagonal line, the models are most accurate in their predictions. The exact location of crossing is at a quality value of 20.0 for the NFQ model, 24.1 for VFQ model and 24.7 for the LQM model. These values are consistent with the distributions annotated quality values, where the majority of fingermark examples are considered to be of lower quality, as shown in Fig. 3.

These experiments show how the feature vector, constructed using the AFQA toolbox, can capture the properties of NFIQ 2.1, VerifingerQ and LQmetric quality assessment methods. Since our toolbox implements the majority of NFIQ 2.1 features, the compatibility between NFIQ 2.1 and our trained model was expected. We do not know how Verifinger calculates their quality values, but the AFQA toolbox features are able to represent the properties of their qualtiy assessment method well. Finally, the LQmetric was designed specifically for assessing the quality of fingermarks and like the remaining 2 methods, our feature vector can capture its properties. This means that the AFQA toolbox features are sufficient for representation of fingerprints as well as fingermarks. These models will serve as as a baseline for the future development of a new, independent, and open-source fingermark quality assessment methods.



(a) VFQ top 3 (b) NFQ top 3 (c) LQM top 3

Fig. 5: **Qualitative comparison between random forest models.** We demonstrate model capabilities based on actual examples from the SD 301 dataset. Ordered from top to bottom, we display fingermark images, which were given highest quality scores by (a) the VFQ model, (b) NFQ model, and (c) LQM model. For each image, we provide scores for all three models in format "MODEL: predicted_value (true_value)". We can observe that the most consistent is the VFQ model, which attributes high value only when clear ridge structure is present.

Qualitative evaluation. For the best performing random forest model, we visualize some of the examples from the test dataset together with their respective predicted and ground-truth quality values. This is shown in Fig. 5. For each model, we show the top three fingermarks based on their predicted quality value.

We begin with the (a) column examples, which the VFQ model considers to be of best quality. All of the examples contain a clear ridge structure, which could be easily recovered with various enhancement methods. The width of ridges and valleys is uniform and the area of the impression is relatively large. In the middle column (b) are top examples based on the NFQ model. Here we see examples with a large amount of high frequency ridge-like formations, which are in most cases not actually friction ridges, but rather specks or smudges. The NFIQ 2.1 method is in essence not intended to be used with fingermarks, which might explain why the trained model cannot differentiate between real ridges and impression distortions. In the right column are top quality examples based on the VFQ model. Here we observe a stronger bias toward fingermarks with a darker average color. It appears that the middle fingermarks contains no recoverable friction ridge, but the LQ-metric falsely detects the high frequency background patterns as friction ridge and consequently assigns to it a high quality value. Another comparison can be made between VFQ and LQM. As discussed, VFQ model assigns good quality to fingermarks with high clarity in the left column (a), but LQM scores for the same marks are more proportional to the area of the visible friction ridge, giving the smaller fingermark a smaller estimate, despite good quality of ridges.

The predicted values for these examples are a relatively close approximation of the ground-truth scores. However, our intent here was not to evaluate the suitability of individual methods for the task of fingermark quality assessment. As apparent from the qualitative results, each method assigns quality based on different friction ridge features, which can result in high differences between scores for a singe fingermark. To leverage the collective power of multiple quality assessment methods, a fusion of predicted scores could improve the overall consistency of the quality assessment process and produce even more objective quality values for fingermarks.

6 Conclusion

In this paper we proposed the AFQA toolbox for fingermark analysis, which contains a large collection of established algorithms, intended for friction ridge feature extraction, as well as various pre-processing for segmentation and enhancement. By making the toolbox open-source, we want to improve the accessibility of existing methods and the reproducibility of future work for the biometric and forensic communities.

We demonstrated the usability of the toolbox by extracting friction ridge features and creating a compact feature vector to represent individual fingermarks efficiently. We then trained three baseline fingermark quality assessment models, based on annotations from existing methods, and evaluated them on a public dataset. The results indicate a high compatibility between the proposed feature vector and the inner workings of existing friction ridge quality assessment methods.

In the future work we plan to expand the toolbox with additional algorithms and better define, what friction ridge properties influence quality the most. We also plan to make use of more contemporary ML methods, such as deep learning, with the objective to further improve the fingermark image quality assessment.

References

[Al07] Alonso-Fernandez, Fernando; Fierrez, Julian; Ortega-Garcia, Javier; Gonzalez-Rodriguez, Joaquin; Fronthaler, Hartwig; Kollreider, Klaus; Bigun, Josef: A comparative study of fingerprint image-quality estimation methods. IEEE Transactions on Information Forensics and Security, 2(4):734–743, 2007.

[As99] Ashbaugh, David R.: Quantitative-qualitative friction ridge analysis : an introduction to basic and advanced ridgeology. CRC press, 1999.

[Ch18] Chugh, Tarang; Cao, Kai; Zhou, Jiayu; Tabassi, Elham; Jain, Anil K.: Latent Fingerprint Value Prediction: Crowd-Based Learning. IEEE Transactions on Information Forensics and Security, 13(1):20–34, 2018.

[CJY04] Chen, Tai Pang; Jiang, Xudong; Yau, Wei-Yun: Fingerprint image quality analysis. In: International Conference on Image Processing. volume 2, pp. 1253–1256, 2004.

[EB18] Ezeobiejesi, Jude; Bhanu, Bir: Latent fingerprint image quality assessment using deep learning. In: Conference on Computer Vision and Pattern Recognition Workshops. pp. 508–516, 2018.

[Fi18a] Fiumara, Gregory; Flanagan, Patricia; Grantham, John; Ko, Kenneth; Marshall, Karen; Schwarz, Matthew; Tabassi, Elham; Woodgate, Brian; Boehnen, Christopher: National Institute of Standards and Technology Special Database 302: Nail to Nail Fingerprint Challenge. Technical Note 2007, National Institute of Standards and Technology, 2018.

[Fi18b] Fiumara, Gregory; Flanagan, Patricia; Schwarz, Matthew; Tabassi, Elham; Boehnen, Christopher: National Institute of Standards and Technology Special Database 301: Nail to Nail Fingerprint Challenge Dry Run. Technical Note 2002, National Institute of Standards and Technology, 2018.

[GM00] Garris, Michael D; McCabe, R. Michael: NIST special database 27: Fingerprint minutiae from latent and matching tenprint images. US Department of Commerce, NIST, 2000.

[HGB19] Haraksim, R; Galbally, J; Beslay, L: Study on Fingermark and Palmmark Identification Technologies for their Implementation in the Schengen Information System. EUR 29755 EN, Publications Office of the European Union, 2019.

[HWJ98] Hong, Lin; Wan, Yifei; Jain, A.: Fingerprint image enhancement: algorithm and performance evaluation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 20:777–789, 1998.

[Ka08] Kaur, Manvjeet; Singh, Mukhwinder; Girdhar, Akshay; Sandhu, Parvinder S: Fingerprint verification system using minutiae extraction technique. World Academy of Science, Engineering and Technology, 46:497–502, 2008.

[KBH20] Kalka, Nathan D; Beachler, Michael; Hicklin, R Austin: LQMetric: A Latent Fingerprint Quality Metric for Predicting AFIS Performance and Assessing the Value of Latent Fingerprints. Journal of Forensic Identification, 70:443–463, 2020.

[LJY02] Lim, Eyung; Jiang, Xudong; Yau, Weiyun: Fingerprint quality and validity analysis. In: International Conference on Image Processing. volume 1, pp. 469–472, 2002.

[MH80] Marr, David; Hildreth, Ellen: Theory of edge detection. Royal Society of London. Series B. Biological Sciences, 207(1167):187–217, 1980.

[Ne98] Neurotechnology: , VeriFinger, 1998. Available online: https://www.neurotechnology.com/verifinger.html. [Accessed 1.6.2021].

[OŠB16] Olsen, Martin Aastrup; Šmida, Vladimír; Busch, Christoph: Finger image quality assessment features – definitions and evaluation. IET Biometrics, 5(2):47–64, 2016.

[SVS13] Sankaran, Anush; Vatsa, Mayank; Singh, Richa: Automated clarity and quality assessment for latent fingerprints. International Conference on Biometrics: Theory, Applications and Systems, pp. 1–6, 2013.

[Sw21] Swofford, H.; Champod, C.; Koertner, A.; Eldridge, H.; Salyards, M.: A method for measuring the quality of friction skin impression evidence: Method development and validation. Forensic Science International, 320:1–13, 2021.

[Ta21] Tabassi, Elham; Olsen, Martin; Bausinger, Oliver; Busch, Christoph; Figlarz, Andrew; Fiumara, Gregory; Henniger, Olaf; Merkle, Johannes; Ruhland, Timo; Schiel, Christopher; Schwaiger, Michael: NIST Fingerprint Image Quality 2, NISTIR 8382. NIST, 2021.

[TWW04] Tabassi, Elham; Wilson, Charles; Watson, Craig I: Fingerprint Image Quality, NISTIR 7151. NIST, 2004.

[Yo13] Yoon, Soweon; Cao, Kai; Liu, Eryun; Jain, Anil K.: LFIQ: Latent fingerprint image quality. In: International Conference on Biometrics: Theory, Applications and Systems. IEEE, pp. 1–8, 2013.