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

Interoperability of Contact and Contactless Fingerprints Across Multiple Fingerprint Sensors

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Abstract: Contactless fingerprinting devices have grown in popularity in recent years due to speed and convenience of capture. Also, due to the global COID-19 pandemic, the need for safe and hygienic options for fingerprint capture are more pressing than ever. However, contactless systems face challenges in the areas of interoperability and matching performance as shown in other works. In this paper, we present a contactless vs. contact interoperability assessment of several contactless devices, including cellphone fingerphoto capture. In addition to evaluating the match performance of each contactless sensor, this paper presents an analysis of the impact of finger size and skin melanin content on contactless match performance. AUC results indicate that contactless match performance of the newest contactless devices is reaching that of contact fingerprints. In addition, match scores indicate that, while not as sensitive to melanin content, contactless fingerprint matching may be impacted by finger size.

Keywords: Fingerprint Interoperability, Contactless Fingerprint, Finger Size, Palm Color.

1 Introduction

The use of fingerprints for identification and verification has been commonplace for many years in commercial, consumer, and government applications. As technology has advanced, so have the methods for fingerprint collection. From inked fingerprints on paper, to contact-based livescan fingerprinting, to contactless fingerprint imaging, while the image capture process may be different, the resulting fingerprint must still be interoperable in matching against legacy contact galleries. Traditional contact-based digital fingerprints impart some degree of elastic deformation on the finger, and consequently, to the ridges of the fingerprint. Contactless fingerprints pose an interoperability problem as they lack the elastic deformation caused by pressing the finger against the capture device [Li18]. In addition, because they are essentially created from fingerphotos, contactless fingerprints may contain high degrees of photometric distortion that, in addition to the lack of elastic deformation, may further reduce matching interoperability [Li18][Li20][Pr21]. The ubiquitous nature of smartphone cameras and their use in multibiometric capture, as well as the emergence of COVID-19 as a major health crisis,

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have driven the need for fast, hygienic capture of contactless fingerprints, making studies of contactless fingerprint imaging interoperability even more necessary. The overall goal of the work presented here is to evaluate the interoperability of multiple contactless fingerprints when matched against contact fingerprints collected from the same individuals. In addition to this baseline interoperability analysis, physiological factors such as skin color and finger size is evaluated to determine their impact on contactless fingerphoto matching. The contributions of this research effort are: 1) a quantification of the interoperability of contactless fingerprints from two contactless devices and one cellphone-based fingerprint collection method against a traditional contact-based digital fingerprinting device, 2) a measurement of the effect of hand size on the overall matching performance of fingerprints, and 3) an exploration of the effect of skin color measured by skin reflectance on the overall matching interoperability and matching performance of contactless-based fingerprints. The results presented here provide critical insight into the application of contactless fingerprinting systems in a variety of biometric scenarios.

2 Background

Two forms of contactless fingerprints were examined in this effort. The first form is contactless fingerprints captured from a standalone kiosk-type sensor that images the finger when in the field of view of the device (see, e.g., [Li18], [Li20], [Th21], [Id21], [Tb21]). The second form is contactless fingerprints that are captured using a cellphone app that employs the built-in camera to capture fingerphotos [Li18]. The images from the cellphone undergo processing to create a binarized or grayscale fingerprint image that are representative of the original fingerphoto captured from the cellphone camera. To evaluate the interoperability of these fingerprints, two commercial 'black-box' fingerprint matchers will be used, along with one open-source matcher. These three solutions rely on minutiae correspondence as the primary method for matching [Ma14], [JRP04].

While the use and capture of contactless fingerprints are relatively new developments, there has been work done to evaluate and use this form of capture with contact-based fingerprint galleries. NIST has provided recommendations on evaluation of contactless fingerprint devices [Li18]. This study outlines the considerations necessary for proper capture of contactless fingerprints, and how these differ from traditional fingerprints.

In addition to best practices for contactless fingerprint applications, there have been other studies into the interoperability of contactless and contact-based fingerprints [Li20], [Bi17], [De18]. These studies have shown the challenges and variability issues that are common when collecting contactless fingerprints. To close the interoperability gap between contact and contactless fingerprints, convolutional neural networks (CNN) that use preprocessed versions of both the contact and contactless prints to perform the matching were demonstrated in [LK19]. An alternative CNN-based method presented in [Da19] uses a pair of CNNs to first find the amount of warp on the contactless fingerprint image, and then use that warp parameter to generate a new version of the contactless fingerprint that is representative of a contact-based fingerprint of the same finger.

Because of the nascent nature and methodology of contactless fingerprinting via photo-

based capture, physiological features that have little to no impact on contact fingerprint collection, such as finger size and skin color, may negatively impact contactless fingerprint interoperability. However, these features have received little evaluation in the literature in this context. Hand geometry features have been used in biometric verification applications. Hand geometry biometrics rely on the hand shape and various parameters of the hand's size as the features to be extracted and compared [SSG00]. Relating to contactless fingerprints, the variation in finger sizes from person to person may have an impact on contactless matching performance when compared to a gallery of contactless images.

Skin tone, also referred to as skin reflectance, is an important factor to consider in face detection and recognition [BM00]. Variations in skin reflectance, as well as differences in lighting, in facial imagery can have a major effect on the outcome of facial recognition and matching. This is typically not an issue when it comes to contact fingerprints because the method of acquisition is not photo-based. Contactless fingerprints, however, rely on fingerphotos to obtain the ridge and valley information of the fingerprint. As with facial images, variation in skin reflectance could have a significant effect on the matching accuracy of the fingerprint extracted from fingerphotos.

3 Dataset Details and Matching Experiments

The fingerprints used in these experiments were collected from 215 individuals who each provided fingerprint data across multiple commercial fingerprint capture devices¹. These devices include one contact device, two kiosk-style contactless devices, and a COTS cellphone-based fingerphoto application. At the request of the sponsor, these devices have been anonymized and will be referred to in this paper as Contact-1, Contactless-1, Contactless-2, and Cellphone-1. Contact-1 is an optical livescan device that captures fingerprints via frustrated total internal reflection (FTIR). Contactless-1 and Contactless 2 are both kiosk-style capture devise. Contactless-1 captures fingerprints using multiple cameras and special illumination while Contactless-2 operates using a single camera and structured light approach. The cellphone devices capture fingerphotos using the integrated cameras and utilize app-specific post processing to convert the fingerphoto to a contact-equivalent image. Sample images from each device are shown in Fig. 1.

¹ This is the first use of this dataset. The dataset is available upon request.



Figure 1: Example of images from contact-1, contactless-1, contactless-2, and cellphone-1

The total number of fingerprint images used in matching experiments was 1,165, consisting of fingerprints from the index, middle, ring, and little fingers only. Thumbs were excluded from the analyses because not every device captured thumbprints. A summary of the number of images from each sensor is provided in Table 1. The dataset also contains finger size data collected from hand geometry images and skin reflectance data measured using the Cortex Technology DSM III sensor [Co21]. Some devices captured images across multiple sessions, with others only capturing one session. In addition, the skin reflectance data collected with the DSM III provided CIEL*a*b* RGB data and a measure of melanin and erythema in the skin [Co21].

Device	Image Type	No. of Samples	No. of Sessions	Total Samples
Contact 1	slaps & rolls	2 slaps 2 thumbs 10 rolls	1	4300
Contactless 1	slaps	2 slaps 2 thumbs	1	2150
Contactless 2	slaps	2 slaps 2 thumbs	2	4300
Cellphone 1	slaps	2 slaps	3	5160

Tab 1: Dataset Description

Before matching, preprocessing was performed on the raw versions of the cellphone-based fingerphotos. The photos were converted to grayscale, histogram equalization was applied, and they were inverted so the ridges are shown as the dark regions of the fingerprint to match traditional fingerprinting techniques. These processed photos, referred to as Cellphone-1-Raw, were matched to provide a comparison of the fingerprint processing done by the COTS application in Cellphone-1. Along with the raw photos, the cellphone-based application provided binarized generated prints from the photos that were also used in matching (i.e., Cellphone-1 images).

Using this dataset, matching experiments were performed on two commercial black-box matchers and one open-source matcher with the segmented slap fingerprints from Contact-1 as the gallery for all matches. The two commercial black box matchers and the open-source matcher are referred to as Matcher-1, Matcher-2, and Matcher-3, respectively. All three matchers were used in an 'out-of-the-box' configuration, with no optimizations made

for contactless fingerprint images. All matches were performed in a one-to-many fashion so that scores were generated for all probes versus all gallery images. The threshold for all matchers was set to 0 to allow all match results to be extracted. As a baseline for the match scores, the rolled fingerprint data that was collected with Contact-1 was matched against the gallery of segmented slaps used for all other matches. Using the results of these matching experiments, receiver operating characteristic (ROC) curves were generated. This was followed by a statistical analysis of the matching results and a statistical correlation of the finger size and skin reflectance data with the matching results.

The analysis of the impact of finger size on contactless fingerprint match performance was performed using the width of the middle finger of the right hand of all individuals. Using this measurement, the finger sizes were split into equal-sized groups and the mated match scores were sorted into these groups to produce a distribution for analysis. The mated match scores were scores obtained by comparing two fingerprint images collected from the same finger. The analysis for the skin reflectance data involved splitting the data into three equal-sized ranges of melanin value using the melanin value provided by the DSM III. From there, a distribution was generated using the mated match scores to evaluate any effect caused by the amount of melanin on the resulting scores.

4 Results

The results shown in Figure 2 shows ROC curves for the contactless devices compared against Contact-1 as well as the baseline match using Contact-1. Along with the contact baseline, there is a 'worst-case' baseline determined using the preprocessed raw images from Cellphone-1 to show a difference in performance when using the binarized images produced by the cellphone app.



Figure 2: Receiver Operating Characteristic for contact and contactless fingerprint devices against Contact-1 using (a) Matcher-1, (b) Matcher-2, and (c) Matcher 3.

The results show a clear distinction in match performance between the three devices that is consistent for the three matchers used. As is shown by the area under the curve (AUC) calculated from the ROC curves, shown in Table 2, Cellphone-1 exhibited the worst matching performance out of the three contactless sensors for the first two matchers, but only by a small margin below Contactless-1. Of the contactless images used in Matcher-

3, Contactless-1 performed the worst with an AUC of only 0.6897.

The match results using Matcher-3 exhibited lower accuracy when compared to the other matchers. All devices performed similarly to the other experiments, except for Contactless-1, which had a much lower matching accuracy, below the performance of images from Cellphone-1. It should be noted that all matchers were used in an 'out of the box' configuration with no optimization for minutiae detection in contactless prints in order to keep the matching results fair.

Device	Matcher-1	Matcher-2	Matcher-3		
Contact-1	1.0000	0.9989	0.9765		
Contactless-1	0.9818	0.9820	0.6897		
Contactless-2	0.9940	0.9955	0.9551		
Cellphone-1	0.9764	0.9635	0.8606		
Cellphone-1-Raw	0.8252	0.7422	0.5964		

Tab 2: AUC of ROC Curves

The results shown in Figure 3 are a comparison of the mated match scores for each of the devices using a specific matcher. In agreement with the ROC curves, the match scores of the two contactless devices trend higher than Cellphone-1, with Contactless-2 achieving the highest match scores.



Figure 3: Comparison of the distribution of mated match scores for each device using (a) Matcher-1, (b) Matcher-2, and (c) Matcher-3.

The results shown in Figures 4-11 are distributions of mated match scores for each device on all three matchers. Each figure shows the distribution all matchers based on either the melanin values or finger width values. For these distributions, the data is into three bins for each device. These bins separate the data based on the melanin measurement obtained from the skin reflectance data collected from the palm of the subjects or the middle finger width calculated for each hand. The threshold values used for these bins were calculated to split the groups into even ranges of melanin amounts or finger width.

For the melanin distributions, these plots show many outliers; however, the overall average area does not indicate a statistically relevant relationship between melanin content and match score. The plots for the melanin value lower than the first threshold do tend to have more outliers at the top end, however, it is apparent that the vast majority of the match scores fall within a similar range for all of the data. As expected, the contact

fingerprint matching data is clearly unaffected by the amount of melanin present. Considering finger width distributions, the middle range of values from 30.99 to 42.17 has the highest-reaching whisker values. In terms of the overall results from this data, Matcher-1 was most affected by finger size for Contactless-1 and Contactless-2, with larger sizes producing higher match scores. For images captured from the other devices, and all images on Matcher-2, there was no noticeable effect of finger width on match scores. For Matcher-3 there was no noticeable effect of the finger width on the matching performance. Along with the width analysis focused on the middle finger, an experiment was also performed using width data for the little finger of the right hand of all participants. The resulting match score distributions showed similar results to the middle finger values, and thus, were not included here.



Figure 4: Comparison of the distribution of mated match scores based on melanin amount using probes from Contact-1 and (a) Matcher-1, (b) Matcher-2, and (c) Matcher-3.



Figure 5: Comparison of the distribution of mated match scores based on melanin amount using probes from Contactless-1 and (a) Matcher-1, (b) Matcher-2, and (c) Matcher-3.





Figure 6: Comparison of the distribution of mated match scores based on melanin amount using probes from Contactless-2 and (a) Matcher-1, (b) Matcher-2, and (c) Matcher-3.



Figure 7: Comparison of the distribution of mated match scores based on melanin amount using probes from Cellphone-1 and (a) Matcher-1, (b) Matcher-2, and (c) Matcher-3.



Figure 8: Comparison of the distribution of mated match scores based on middle finger width using probes from Contact-1 and (a) Matcher-1, (b) Matcher-2, and (c) Matcher-3.



Figure 9: Comparison of the distribution of mated match scores based on middle finger width using probes from Contactless-1 and (a) Matcher-1, (b) Matcher-2, and (c) Matcher-3.



Figure 10: Comparison of the distribution of mated match scores based on middle finger width using probes from Contactless-2 and (a) Matcher-1, (b) Matcher-2, and (c) Matcher-3.



Figure 11: Comparison of the distribution of mated match scores based on middle finger width using probes from Cellphone-1 and (a) Matcher-1, (b) Matcher-2, and (c) Matcher-3.

5 Conclusion

This work explored the interoperability of fingerprints captured from multiple contactless fingerprint devices matched against a gallery of fingerprints captured using a contactbased fingerprint device. Based on the results shown, the Contactless-2 device outperformed both Contactless-1 and Cellphone-1, with an AUC of 0.9818, 0.9955, and 0.9551 for Matcher-1, Matcher-2, and Matcher-3, respectively, with the latter two performing within 0.0176 and 0.0185 of each other for Matcher-1 and Matcher-2, respectively. Using Matcher-3, Contactless-1 fell below Cellphone-1 by a margin of 0.1709. Again, this performance is likely due to the lack of optimization done for Matcher-3. The Cellphone-1 images outperformed the baseline Cellphone-1-raw images by a margin of 0.1512, 0.2213, 0.2642 based on the AUC, as expected.

After the matching analysis was completed, an evaluation of the impact of skin color, collected via skin reflectometer, on match performance was conducted. From this skin reflectance data, a measure of the melanin present in the palm of the subjects was used to split the match scores into groups. This was used to generate new distributions to show the performance for each group. Based on these distributions of the results, there was no perceivable impact across all of the experiments based on statistical significance. This also shows that the contact-based fingerprints were unaffected by melanin content, as was the expected outcome.

A similar analysis was performed for finger size using the width of the middle finger from the right hand of each participant. Again, the data was split into groups based on finger width data, and the match results were used to generate a distribution to convey the performance of the matching based on the various widths. In this case, there was a noticeable effect on the match scores of Contactless-1 and Contactless-2 when using Matcher-1. This effect was not present in either Contact-1 or Cellphone-1 images used as probes to the same matcher, nor was it observed with probes images from any of the devices matched by Matcher-2 or Matcher-3.

Based on the results of this work, it has been shown that contactless fingerprint devices, such as Contactless-2, can achieve a match performance approaching that of contact fingerprints. In comparison to previous work from [Li20], Cellphone-1 with an AUC of 0.9764, 0.9635, and 0.8606 from Matcher-1, Matcher-2, and Matcher-3 respectively outperforms similar cellphone-based device performance. As well, Contactless-1, while not matching the results of Contactless-2, exceeds the match performance results of many of the devices from [Li20] as well.

This material is based upon work supported by the Center for Identification Technology Research and the National Science Foundation under Grant No. 1650474.

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