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Investigating the impact of demographic factors on contactless fingerprint interoperability

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Abstract: Contactless fingerprints have continued to grow interoperability as a faster and more convenient replacement for contact fingerprints, and with covid-19 now starting to be a past event the need for hygienic alternatives has only grown after the sudden focus during the pandemic. Though, past works have shown issues with the interoperability of contactless prints from both kiosk devices and phone fingerprint collection apps. The focus of the paper is the evaluation of match performance between contact and contactless fingerprints, and the evaluation of match score bias based on skin demographics. AUC results indicate contactless match performance is as good as contact fingerprints, while phone contactless fingerprints fall short. Additionally, bias found for melanin showed specific ranges effected in both low melanin values and high melanin values.

Keywords: Fingerprint, Contact, Contactless, Interoperability, Melanin, Ethnicity, Demographic.

1 Introduction

With continued advances in mobile device camera technology in, the ability to extract fingerprints from digital fingerphotos has become a reality, with smartphone multi-modal biometric capture platforms becoming replacements for traditional kiosk-style sensor devices. These devices offer a high-throughput, hygienic means of capturing fingerprints. Though, the contact-based capture methods (livescan, ink & paper, etc.) used to compile most legacy fingerprint datasets cause elastic deformation, while fingerphotos often have significant photometric distortion, nonuniform focus, motion blur, etc. [LG18]. Most of the previous works on improving interoperability between contact and contactless fingerprints have focused on addressing the challenge by developing new matching and comparison schemes, such as imparting the elastic deformation in contact prints onto contactless prints [LG18], implementing specialized convolutional neural networks (CNN) focused on deformation correction [SU21], and implementing a CNN using an attention module for detecting minutiae [GE21].The goal of the work presented here is more fundamental than previous work in that it aims to evaluate how demographic factors, specifically skin color, impact contactless fingerprint interoperability. The contributions of the resulting research effort are: 1) Quantification of the comparison score interoperability of four contactless fingerprint modalities in a new contactless dataset - two datasets from kiosk style devices, and two datasets from mobile phone applications, each recorded twice on different phone models, for a total of six contactless fingerprint datasets, 2) An exploration of the effect of skin pigmentation measured by skin reflectance on the comparison interoperability of contact and contactless fingerprints.

2 Previous Work

The US National Institute for Standards and Technology (NIST) has released a document pertaining to the guidance of evaluating contactless fingerprints [LG18], and an additional document directly pertaining to the interoperability of contactless-to-contact fingerprints [TK21]. The NIST interoperability report extends much of the guidance to include the comparison of contact and contactless images by suggesting fair metrics that can be used to directly compare the different types of prints to gather a quality assessment of the fingerprints by scoring differences in the minutiae [TK21]. Outside of best practices, convolutional neural networks (CNN) have commonly been used. contactless fingerphotos and contact fingerprints were matched using a CNN with attention by training the model to match prints by aligning the minutiae of prints and compared the results against a COTS matcher and another CNN Siamese model [GE21]. A second application of a CNN Siamese network was reported to attempt matching between contact fingerprints and contactless fingerphotos by incorporating contextual information learned by the network for the minutiae feature correspondence [LG20]. Differential performance of biometric approaches among various age, gender, and ethnic demographics is a current area of concern in the field. As part of maintaining equitable performance across all members of a target population, the impacts of how of demographic under-representation in a dataset can lead to differences in facial recognition accuracy must be understood (see, e.g., [LK19], [CH19], [HSV19], [KA20]). In [CH19], a facial recognition experiment that considered skin reflectance found lower reflectance values had lower average comparison scores than higher reflectance values. A different work attempting to remove female characteristics from fingerprints for de-identification to reduce unauthorized disclosure [GLJ21] showed differences in male and female energy concentrations at select frequency bands. Because contactless fingerprints are often captured using photographic methods, the same performance challenges impacting facial recognition may also negatively impact contactless fingerprint interoperability with legacy contact-based galleries. A previous work in [LM14], evaluating the effect of melanin values on comparison scores from fingerprints captured using cellphones, showed no perceivable impact on match score. However, a different study [WM21] tested differential performance using a COTS fingerprint matcher and a neural network matcher using a contact fingerprint, and results showed that performance varied on both matchers based on self-

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reported ethnicity. In [GG22], match performance for both different ethnicities and ages was evaluated, with results showing that performance varied based on ethnicity. Caucasians had a higher accuracy for fingerprints from right index fingers than non-Caucasians, while exhibiting lower accuracy for right thumbs. When considering different age ranges, [GG22] found that, as age increased, so did accuracy. The study presented in [TK21] showed the opposite; a decrease in match performance with age when attempting to match fingerprints taken from the same individual over at least five years.

3 Dataset and matching experiments

Age Group	
18 - 19	87
20 – 29	354
30 – 39	43
40 – 49	5
50 – 59	8
60 – 69	2
70 – 79	1

Ethnicity	Melanin Range	Male	Female
African American: 10	29.88 - 56.43	5	5
Caucasian: 379	16.52 - 48.52	144	235
East Asian: 27	27.57 - 47.41	14	13
Hispanic: 34	23.86 - 38.52	14	20
Indian: 5	30.52 - 49.69	4	1
Middle Eastern: 25	23.64 - 41.44	17	8
Native American: 1	29.73	1	0
Pacific Islander: 2	29.87	0	2
Other: 17	26.15 - 55.55	7	10
All: 500	31- 56.43	206	294

Tab. 1: Dataset Demographic Information

A data collection was conducted to obtain the data used in this effort (Institutional IRB# 2001870127). Fingerprints were collected from three different device types for this data collection: 1) optical and thin-film transistor livescan devices, 2) two different stand-alone contactless kiosk devices (see, e.g., [LG18], [TK21]), and 3) cellphone cameras using two different commercial apps made for the android operating system that detect, capture, and segment finger photos. Each app performs its own 'black-box' post-processing to create a 'contact equivalent' fingerprint image. The resulting dataset used for the experiments was collected from a total of 500 individuals. A breakdown of demographic information is provided in Tab 1, along with the measured palm melanin range of each ethnicity. Skin reflectance readings were taken using the Cortex Technology DSM III sensor. Four measurements were taken for each subject: two on the palm of the hand, and two on the back of the hand. The first palm measurement was used for observations, and skin reflectance measurements were measured using CIEL*a*b* color space with an additional Melanin and Erythema reading [GRR10]. In total, there are twelve unique captures for every subjects' fingerprints. Two of the captures are from kiosk-style contact fingerprint devices, two captures are from kiosk style contactless fingerprint devices, and two captures are from two different COTS cellphone apps that were used on two different cellphone models: the

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1. The dataset is available upon request.

Samsung S20 and S21. The sensor devices have been left anonymous at the request of the sponsor, and will be referred to as Contact-1, Contact-2, Contactless-1, Contactless-2, PhoneA1, PhoneA2, PhoneB1, PhoneB2. PhoneA is the Samsung S20, and PhoneB is the Samsung S21, with ‘1’ and ‘2’ in the sensor name referring to the different apps. Contact-1 uses a light emitting sensor (LES) on the contact plate and a CMOS camera to capture the impression. Contact-2 is an optical livescan device that uses frustrated total internal reflection (FTIR). Contactless-1 captures fingerprints using multiple cameras and special illumination. Contactless-2 uses a single camera and records fingerprints using structured light. Both cellphone apps use the phone camera to take pictures of the subjects’ hands, then performs proprietary processing and segmentation to create the contact equivalent image. Only the four fingers on the left and right hands were considered in the analysis because some contactless capture devices/apps did not collect thumb images. For all matching experiments, the gallery used was the segmented four-finger slap fingerprints from the Contact-2 device. The matching was performed using all other sets as the probes against the gallery, for a total of twelve unique experiments. The matcher used was the Innovatrics fingerprint matcher version 7.6.0.627, which is optimized ‘out of the box’ for matching contactless fingerprints.

4 Results

As a baseline for any comparisons made, the segmented four-finger slap captures from the Contact-1 device were matched against the same from Contact-2. Match results are shown in Tab. 2 as the Area Under the Curve (AUC) value calculated by comparing the true match rate and false match rate of each matching between the listed dataset and the Contact-1 slaps.

Dataset	AUC
Baseline	0.9940
Contact-1 Roll	0.9787
Contact-2 Roll	0.9937
Contactless-1	0.9700
Contactless-2	0.9934

Dataset	AUC
PhoneA1	0.9639
PhoneA2	0.9131
PhoneB1	0.9681
PhoneB2	0.9507

Tab. 2 Match Score AUC Values

The AUC values show near equal performance between contact and contactless datasets with the AUC ranging from Contactless-1 at 0.9700 to Contact-2 Roll at 0.9937, with only the baseline higher with 0.9940. The phone apps show a drop in performance compared to both the contact and contactless datasets, with the highest AUC value 0.9681 from PhoneB1 to 0.9131 from PhoneA2. Between PhoneA and PhoneB models, app 1 had only a slight drop in AUC of 0.0042, while the drop in AUC for app 2 was larger at 0.0376, with PhoneB with the

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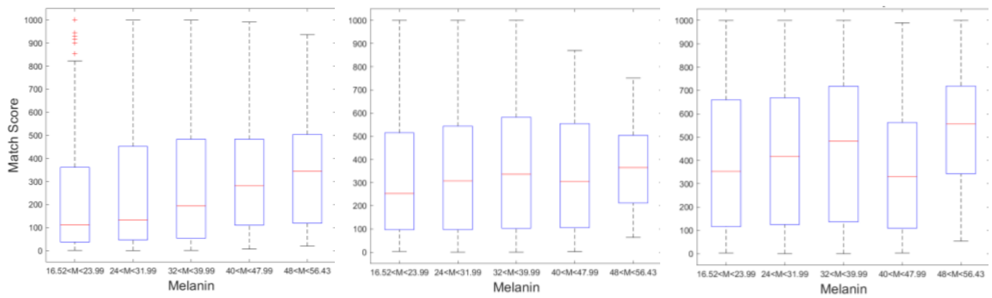
higher AUC for both apps.

An analysis of the impact of skin reflectance on comparison score was performed using the measured palm melanin values indicated in Tab. 1. As can be seen in the measured palm melanin ranges, there is a high degree of overlap in values among the self-reported ethnicities groups for the dataset, indicating that ethnicity is not necessarily an absolute indicator of skin color. The melanin range for Caucasians spans from 16.52-48.52. East Asian, Middle East and Hispanic all have a melanin range that is fully overlapped by the Caucasian range. African American and ‘Other’ are the self-reported ethnicities with melanin values above the Caucasian range, with a maximum value of 56.43 and 55.55 respectively.



(a) (b) (c)

Fig. 1 Match Scores VS Melanin Contact (a) Contact-1 Roll (b) Contact-2 Roll (c) Contact-2 Slap

Results relating 5 discrete melanin content ranges to comparison score are illustrated in Fig. 1-3 as boxplots, with each division of melanin range containing an equal range of melanin values. Fig. 1 shows the melanin values against the match scores for the contact sets. Fig. 1(a) illustrates that the Contact-1 Roll average match score in each melanin range slightly increases with the melanin value, which is also observed in both Fig. 1(b) Contact-2 Roll and Fig. 1(c) Contact-2 Slap boxplots, except for the 40-47.99 range. Fig. 2 shows the melanin values against the match scores for the contactless sets. Fig. 2(a) indicates no noticeable differences in scores for the Contactles-1 kiosk device across all melanin ranges evaluated. In Fig. 2(b), it is observed thatContactless-2 has higher overall comparison scores for all melanin ranges than those shown for Contactless-1 in Fig. 2(a). Fig. 3 shows the melanin values against the match scores for the images collected with the cellphone apps. Fig. 3(d) indicates a noticeable increase in accuracy for the highest melanin range compared to the other ranges, being nearly equal except for a slight dip in accuracy for the second-highest melanin range.

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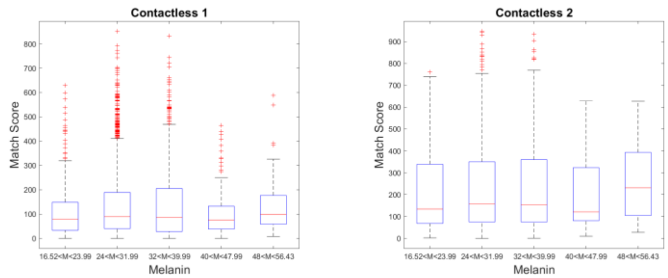
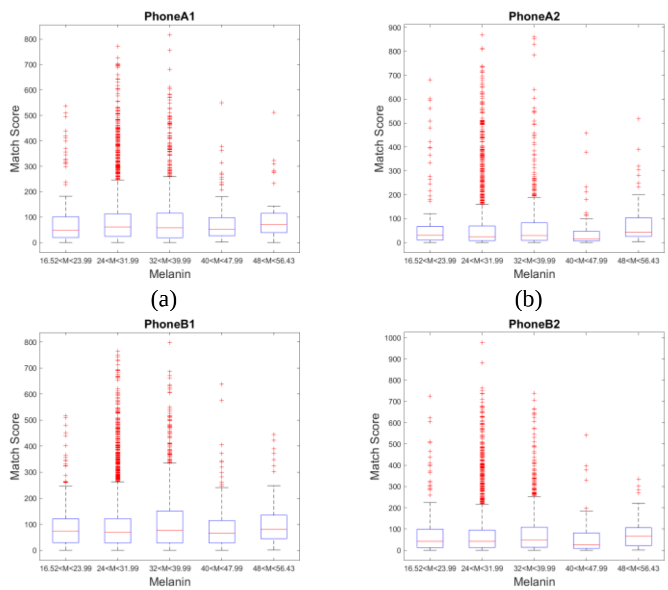


(a) (b)

Fig. 2 Match Scores VS Melanin Contactless (a) Contactless-1 (b) Contactless-2



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

Fig. 3 Match Scores VS Melanin Phone (a) PhoneA1 (b) PhoneA2 (c) PhoneB1 (d) PhoneB2

Fig. 3(a)-(b) also show an increase in average for the highest melanin range, though not as much as Fig. 3(d). Fig. 3(c) shows a negligible increase in accuracy for the highest melanin range with no other noticeable trends. These observations of variable performance for the higher melanin range may be due to the low number of individuals with this range in the dataset.

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5 Conclusions

The evaluation of melanin content of all the individuals in the dataset versus the comparison scores show some differences, though the demographics in Tab. 1 indicates a high degree of overlap in measured melanin values, with participants self-reporting as Caucasian having a melanin range overlapping all other self-reported ethnicities, with only African American, and Other not fully overlapped. As shown in Fig. 1(a) & (b), comparison scores from both contact roll sets indicate the lowest melanin range exhibited the lowest average match score. As shown in Fig. 1(c) for Contact-2 Slap and Fig. 2 for both contactless sets, the lowest melanin range tied with the fourth-highest range for the lowest average match score. Additionally for all contact and contactless datasets, average match score slightly increased with melanin content until the fourth highest range where the average dropped slightly except for Contact-1 Roll. This was followed by an increase in accuracy for the highest melanin range, with the highest accuracy for all contact and contactless sets indicating a slight bias against the melanin range 16.52-23.99 and 40-47.99, and a bias for the melanin range 48-56.45. As shown in Fig. 3, the cellphone images did not show the same trend, with lower melanin values performing worse However, the highest melanin range performed as well or slightly better than all other ranges for that set, and the second highest range did only as well or slightly worse than all other sets similar to the contactless and contact observations, indicating the same bias for those two ranges. The bias found is likely due to a lower number of participants for those ranges since match score tend to be higher when there are less samples.

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