

Contactless Fingerprints: Differential Performance for Fingers of Varying Size and Ridge Density

Abstract: The match performance of contactless fingerprint probes compared to contact-based galleries has increased accuracy. This performance, along with convenience of use, is encouraging the utilization of contactless fingerprint collection methods. However, issues with differential performance for different demographics may still exist. Past works focused mainly on the interoperability of contactless prints with smartphone applications and kiosk devices. This paper focuses on the differential performance of genuine match scores based on the demographic of finger size, ridge density, and total ridge count. Distribution of genuine match scores shows a correlation between an increase in genuine match scores and these variables in contactless smartphone collection methods with the largest correlation appearing in finger size.

Keywords: Fingerprint, Interoperability, Contact, Contactless, Finger Size, Ridge Density

1 Introduction

The advancement of camera capture quality for mobile devices has sparked interest in the use of these devices as contactless fingerprint capture tools. Smartphones allow for a portable and quick collection that is more accessible and convenient than traditional standalone sensors. Along with this newfound interest comes the set of challenges that are linked to the optimization and accuracy of contactless fingerprints compared to their contact counterparts. These contactless fingerprint tools typically generate a contact equivalent fingerprint, obtained from the fingerphoto, for subsequent matching attempts. Contactless fingerprint imaging systems have been found to have distortion and loss of information, image clarity, and greyscale variations, which tends to be an issue caused by the difference in lighting based on the collection location. Due to the limited amount of datasets available for contactless fingerprints, research has focused on the interoperability of contactless and ink or liveness contact-based fingerprints is limited [MP17]. Other works have reported challenges arising from low ridge/valley contrast, non-uniform illumination, perspective distortions from non-uniform collection distances, differences in the finger orientation, and lack of cross-compatibility when matching against legacy datasets [Gr22]. The purpose of the study presented here is to evaluate the effects caused by finger size and ridge density in the interoperability of contact and contactless-based collection methods. Contributions in this paper are 1) an analysis of the correlation between finger size and ridge density in contactless fingerprint datasets, and 2) an analysis of the impact of finger size and ridge density on genuine match scores when matched against a contact dataset. These results will lend critical insight into how finger scaling in collection apps can impact the performance of contactless fingerprints.

1.1 Related Works

There have been two main areas of research in the field of contactless fingerprint technology; differential performance and interoperability between contact and contactless images. The research field of contactless fingerprints has mainly been focused on interoperability since legacy contact-based datasets requiring this functionality. Beyond matching contactless probes to legacy contact galleries, demographic factors have also been explored to determine which variables can influence contactless match scores [Gr22, BND22]. These demographic factors were skin color, skin texture, keratin levels, pigmentation, temperature, elasticity, and finger minutiae. To date, no linear relationship between any of these demographics and match performance has been observed. However, there was a strong correlation between the image quality and match scores observed in [HE16]. Enhancement of fingerprint images has been a major area of study for both contact and contactless fingerprints because distortion generally causes high FNMR [MS16]. Enhancement techniques can be simple, such as removing noise from slap fingerprints to allow for accurate segmentation [RM11], to complex, such as using deep learning to unwarp contactless fingerprint images [Da19]. Finger size has been investigated with differing results. Previous research that investigated the influence of finger size on the interoperability of contactless fingerprints with the acquired match scores against contact-based devices found that there was a correlation between finger size and match scores with one of the matchers evaluated [Wi21]. However, the finger sizes were only separated into two distinct ranges, large or small, and it is difficult to determine the actual effect of finger size with only two subjective and qualitative size variables. This concept was examined in another study that compared fingerprints from smartphones to legacy slaps and found a TAR of 95.79% and a FAR of 0.1% while the baseline using contact-based methods was a TAR of 98.55% with an equal FAR of 0.1% [De18]. An issue that could cause variation in match performance is finger orientation. One study observed variations of match scores based on finger orientation, with results indicating that pose correction caused a decrease in EER and a 9.93%, 10.20%, and 74.97% improvement in rank 1 accuracy from three respective databases [TK20]. Ridge density is the spacing of individual ridges in a fingerprint and is a unique trait that is commonly used for its uniqueness in anti-spoofing liveness detection [AS06]. Contactless fingerprints present a challenge when considering ridge density because of the curvature of the finger when taking the image leads to perspective distortion of the ridges on the periphery of the finger. A resolution of 500 ppi is the minimum sampling rate required, but this causes under-sampling of the edges, so the US National Institute of Standards and Technology (NIST) recommends a 700 ppi sampling rate to accurately capture the edges [Li18].

1.2 Dataset and Measurements

The dataset that was utilized for this research¹ consists of contact fingerprints,

¹ Dataset is available upon request.

contactless fingerprints, and hand images. The devices used to collect this data were the Guardian and Kojak for contact fingerprints, Gemalto and Morpho Wave for contactless kiosk capture images, and two third-party apps, on the Android Galaxy S20 and Android Galaxy S21 for contactless fingerprints. A commercial digital camera was also used to capture hand geometry images. The largest demographics for these collections consisted of 20–29-year-old Caucasians. To ensure the uniformity of the measurements, a custom interface was created to measure the width of the first joint closest to each fingertip in the hand geometry images as a baseline finger size measurement (Fig. 1(a)). Finger size distribution is provided in Fig. 1(b), with most finger sizes being between 15 mm and 17 mm in width. Finger size distributions are shown in Fig. 1.

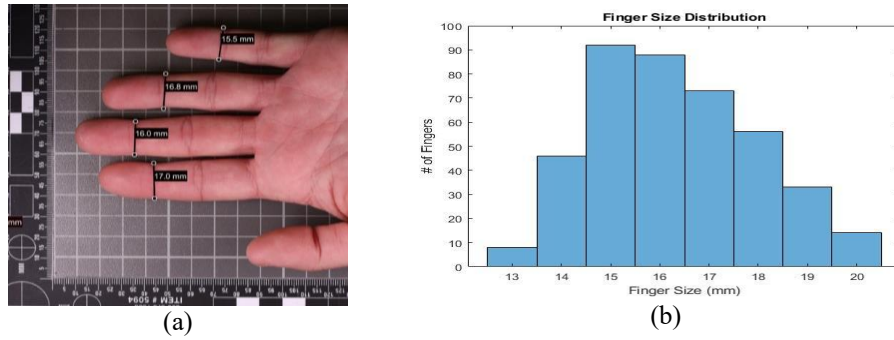


Fig 1. Finger Size Distribution Chart (a) and Finger Size Program Result in mm (b)

Ridge density was determined in MATLAB by gathering datapoints using images that were collected with the contact-based Kojak device, since they were the baseline for generating match scores. The *regionprops* command was used with the *centroids* parameter to find the center of mass of each image. Multiple centroids were found and averaged to find the horizontal and vertical center of rows of the fingerprint image. Then, the edge detection was done using a Sobel filter with the *edge* function, an example of a centroid image and an edge-detected image are shown in Fig. 2(a) and Fig. 2(b), respectively. Finally, the pixel values at the rows and columns were stored in arrays that were iterated to count the number of ridges in the image that were detected. Fifteen pixels were counted in both the positive and negative direction in both rows and columns to count the ridges. Once the ridges were accounted for, the individual arrays were divided by 2 since the edge detection method counted both the start of the ridge and where it ended. These values were averaged to get a ridge value for each fingerprint. For the ridge density calculation performed in this study, only horizontal ridges (with respect to the orientation of the fingers in the hand photos) were utilized, because the finger measurements were only the width of the finger. The flatter the participant's finger was on the capture platform resulted in more data being collected, increasing the ridge count number. This adds a third variable to be considered: ridge count in each individual

capture. For this purpose, total ridges, regardless of direction and finger size, were counted to see the impact of total ridges on genuine match scores. The matcher utilized was the Innovatrics fingerprint matcher version 7.6.0.627, which is a consumer off the shelf system optimized for matching contactless fingerprints.



Fig. 2: Uncropped Input Image with Centroids (a) & Sobel Edge Detected Fingerprint (b)

2 Results

Understanding the relation between fingerphoto ridge density and finger size is imperative to understanding the impact that they influence the genuine match scores. Ridge density was found for each finger by dividing the number of horizontal ridges by the size of the finger, with the resulting values ranging from 0.19 to 1.45 ridges/mm. Fingers were separated into 10 bins based on their ridge density value where each bin is 0.05 ridges/mm in width. In this dataset, there does appear to be a correlation in the relationship between the two variables of finger size and ridge density. This relationship is a positive linear function, as the finger size increases the ridge density increases, with the difference in the average for the smallest finger size bin and the largest finger size bin being over 3 units of ridges per millimeter. The Kojak device fingerprints were used as the gallery and matched against the other devices to produce the match scores to associate with finger size and ridge density. The middle range of sizes do not appear to have a correlation between the finger size and match score, but there is a noticeable difference at both the lower end (13mm and 14mm) and upper end (19mm and 20mm) shown in Fig. 3.

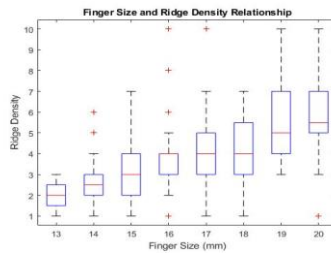


Fig. 3: Finger Size and Ridge Density Relationship

No statistically significant correlation between the three variables investigated and genuine match scores was observed in the baseline Guardian vs. Kojak matching experiment. The smallest finger size had a maximum genuine score below 700, but every size above this had genuine scores over 900, with similar results for all three variables, as shown in Fig. 4 and Fig. 5. This result is to be expected due to the maturity of contact-based fingerprint collection and matching.

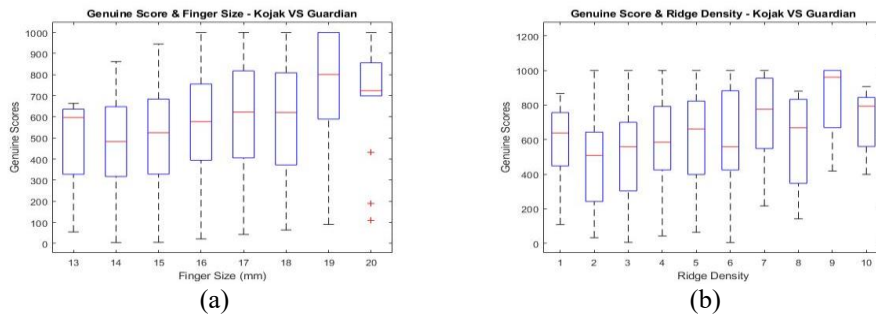


Fig. 4: Genuine Score Against Finger Size (a) & Ridge Density (b) Contact-Based Guardian

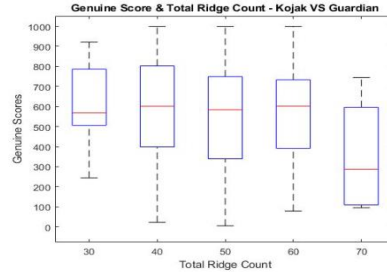


Fig. 5: Genuine Score Against Total Ridge Count Contact-Based Guardian

For the contactless kiosk fingerprint images, there were varying results between the two devices. The median values were consistent for all three variables for the Gemalto device, but they had different maximum match scores, while the Morpho device had similar results to the contact-based method with no correlations observed between the genuine scores and any of the three variables. The fingerprints captured using smartphone apps produced results that displayed a correlation between finger size, ridge density, and genuine match scores. The results had variation based on which of the two applications were used. However, between the two models of cellular devices, there was little variation. Application A results were similar to the contactless Gemalto results for the finger size variable. As finger size increased, the median stayed consistent but the maximum score increased. The ridge density plots displayed no correlation between finger size and ridge density for the fingerprints that were captured with application A.

The ridge count plots had a variation in the smallest bin of ridge count between the two devices, which could be caused by a capture issue, such as finger orientation. Application B displayed the highest correlation between genuine scores, finger size, and ridge density. The results between each model of the cellular device had little variation, as observed in application A. Application B finger size and genuine score plots showed the most apparent correlation between finger size and genuine match scores. Genuine scores for fingers sizes between 13 mm and 16 mm had exceptionally low genuine match scores, but for 17 mm and up, the genuine match scores started to drastically increase with finger size. There seemed to be a correlation between ridge density and genuine match score. As ridge density increases there is a slight increase in genuine match scores averages. There was a significant quantity of outliers for the smaller ridge density bins. For ridge count, it appears that lower ridge counts were correlated with a higher average match score, but the middle range of ridge counts had many outliers that were above the average value. The results for each smartphone are displayed side by side for each variable and application in Fig. 6 through Fig. 11.

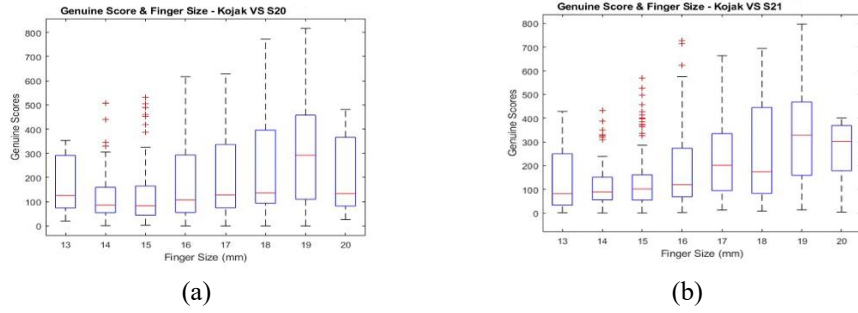


Fig. 6: Genuine Score Against Finger Size App A S20 (a) & S21 (b)

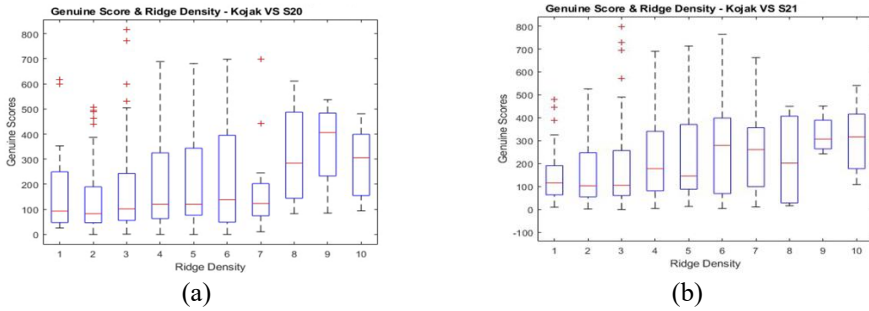


Fig. 7: Genuine Score Against Ridge Density App A S20 (a) & S21 (b)

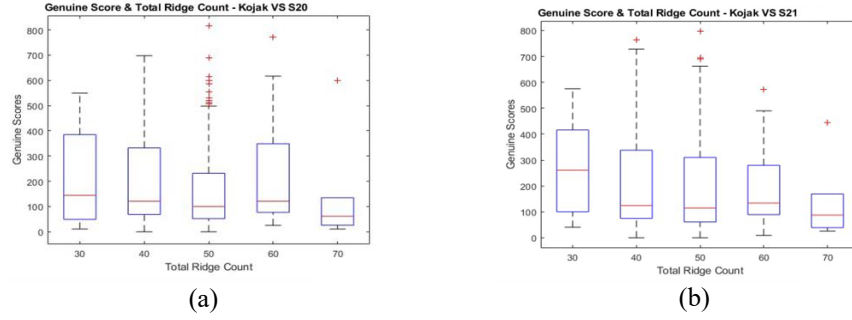


Fig. 8: Genuine Score Against Total Ridge Count App A S20 (a) & S21 (b)

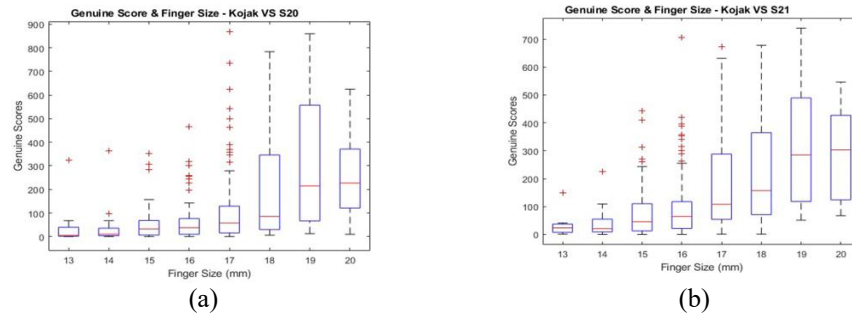


Fig. 9: Genuine Score Against Finger Size App B S20 (a) & S21 (b)

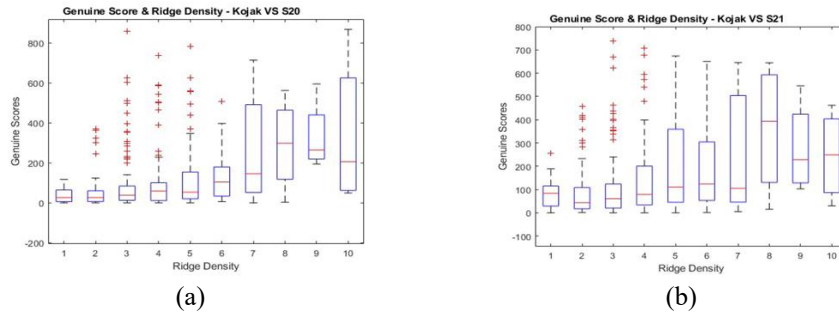


Fig. 10: Genuine Score Against Ridge Density App B S20 (a) & S21 (b)

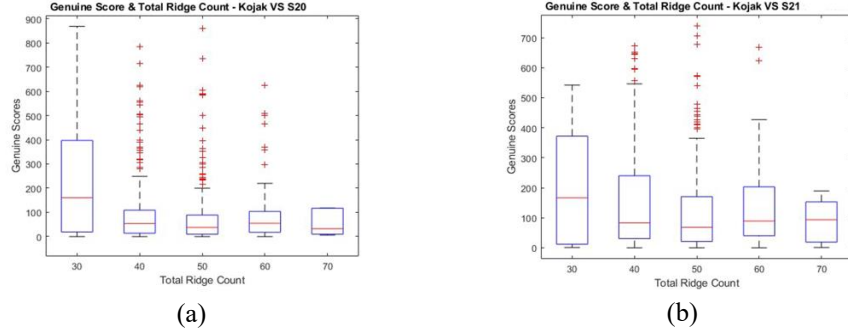


Fig. 11: Genuine Score Against Total Ridge Count App B S20 (a) & S21 (b)

3 Conclusion

Ultimately, these results provide evidence that there is a correlation between finger size and match scores, specifically in contactless fingerprints compared to contact-based prints. It is difficult to accurately determine the total effect that they have on the match score due to the low number of data available at the smallest and largest bins present in the contactless dataset used for this study. The smallest finger size bins typically displayed comparatively low genuine scores, while the scores increased and stayed relatively consistent at sizes of 15 mm and up. The smallest finger sizes did have the most variation between the different devices, and further investigation is needed to determine the cause of this. In a similar fashion, ridge density showed the same trend as the finger size result with little to no correlation in each case except the cellular device fingerprint images. The total ridge count appeared to have little to no correlation across any device. The observation of fingerprints captured using smartphone apps resulted in the highest variability in results expected because this is the newest modality and has had little time for optimization and refinement. These results have major implications on how contactless fingerprint app developers scale finger images prior to image processing to produce a contact-equivalent image. To further this research, these experiments need to be performed on a larger dataset consisting of more variability in finger size, specifically containing exceptionally large and small fingers. The distribution of finger sizes will most likely retain the same distribution observed in this study based on the average finger sizes, but it is desirable to have more data to have a higher sample of the outliers in finger size.

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