Toe Prints: An Application Study for Biometric Verification in Adults

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Abstract

Biometric recognition systems provide an easy way to verify an individual's identity through physiological and behavioral biometric traits, due to the persistence of these traits. The physiological traits are extensively utilized to secure the applications of numerous fields. Among these, toe print is one of the physiological traits that has been discussed and evaluated for the children; however, it has not been addressed in the past as this can also be utilized to verify the identity of an adult, especially for a person with different abilities. In this paper, we have come up with a feasibility study of toe prints while comparing them with the impression of a person's different fingers in terms of the overall performance of a biometric verification system. To accomplish this task, the toe print database is collected from different persons of age varying from 17 years to 64 years, which is the first database of its kind and is made available in public domain. Fingerprint impressions are also collected along with the toe print to compare the reliability of the toe print with respect to performance using a standard fingerprint verification tool. Verifinger trial version has been utilized by considering the two standard fingerprint verification protocols viz. 1-vs-1 and FVC to assess the performance of the toe print verification system in terms of the equal error rate (EER). The toe print verification system attains 0.04% and 0.01% EER values for 1-vs-1 and FVC protocol, respectively, which clearly depicts the feasibility of toe print as a potential biometric trait.

1. Introduction

Biometric recognition is a system of verifying the identity based on the physiological and behavioral trait/attributes of a person [7, 8]. Fingerprint, face, ear, etc., are the physiological attributes and the behavioral attributes include the gait, signature, etc. In these systems, features of a biometric trait are extracted and securely stored in the database in the form of a user template, and this stage is known as enrollment. Again, at the time of verification, features are extracted from the query biometric trait and compared with the stored template to establish the identity match/non-match. Nowadays, authentication systems based on biometrics, especially fingerprints, are primarily utilized instead of traditional authentication systems based on password/pin. The reason behind this exploitation is the benefits that biometric authentication systems provide over the traditional systems, such as ease to capture, the persistence of biometric traits, and no need to remember, unlike password-based systems. Besides, biometrics can provide a solution to identify a person with different abilities using biometric traits, which always easy to provide compared to traditional systems for such persons.

Toe print is also a potential physiological attribute of a person for the identification task. Toe print contains similar ridge patterns as the fingerprint impression as well as exhibits unique features (minutiae points) to differentiate the identity of a person from another. In the past, the footprints have been used for verification of children [16]. The use-case of footprint for grown-up children and adults is not feasible as the size limitation of acquisition sensors. Nevertheless, toe print can easily be acquired from standard fingerprint sensors, making toe print one of the possible biometric traits. The applications of toe print for biometric identification/verification can be significant for a person with different abilities. The area of toe print (big toe print) is larger than that of fingerprints, so it may contain more information (*e.g.* more minutiae points) as compared to the fingerprints. In addition, the foot of a person is generally covered; therefore, the possibility of leaving a toe print impression to any surface is negligible as compared to fingerprint, which makes this modality highly secure.

The following are the primary motivations for introducing toe print as a biometric trait:

- Genetic defects (Adermatoglyphia [3]) cause people to lose their fingerprints, and in some cases, they are not shaped properly (Hand Symbrachydactyly [13]).
- Individuals lose fingers in automobile accidents, civil constructions, and at-home injuries. According to data, over 30,000 children and adults had their fingers amputated in doors and power tools [4].
- In addition, the widely used fingerprint biometric system can be easily adapted to authenticate a user using toe prints. The authentication process does not necessitate the use of any additional hardware. In some countries such as India (Aadhaar program), citizens are authenticated using biometric traits, and the most common of which is the fingerprint. Toe prints can serve as an option for those who do not have fingerprints.

This paper presents a performance analysis to show the usability of toe print as a possible biometric trait for use-cases mentioned above by comparing it to a person's fingerprint impressions. This clearly depicts that the toe prints are capable of differentiating the identity of a person as much as a fingerprint or, per se, other biometric traits do. To evaluate the performance, a new toe print database has been collected, which is the first of its kind, along with the fingerprint impressions by considering a standard fingerprint verification method (i.e., Verifinger demo [12]). Some of the toe print samples and different fingerprints are shown in Figure 1. Also, an example of representing the minutiae points, especially of the toe print, is depicted in Figure 2.

The rest of the paper is organized as follows. Section 2 discusses some of the past work where the application of footprint and toe print for children has been discussed. To establish the fact that the toe print can be used as a potential biometric trait, the complete experimental analysis has been discussed in Section 3. Section 4 concludes the paper and presents some of the future scopes.

2. Related Work

In biometrics, a lot of work has been done related to the fingerprint biometric trait due to the feasibility of fingerprint for all the aspects of an authentication system based on fingerprint [10]. However, this does not work properly to identify the infants (e.g., for vaccination, identifying the lost child, etc.) due to the limitation of the available sensor's capability to capture the infants' fingerprints, and their fingerprints are not grown enough so that they can be used to store as a unique biometric data. To address this limitation, some works in the literature suggest the use of footprints as biometric data for infants. Nevertheless, a database has been proposed in [6], which utilizes infants and toddler fingerprints for identification tasks for vaccination purposes. The verification accuracy has been tested on commercial and latent fingerprint SDKs. In [9], an approach has been proposed to identify the infant by using the footprint instead of a fingerprint. The main reason behind this is that the footprints are easy to capture for an infant as compare to the fingerprint as well as improve the performance. In this work, the footprint database of infants and newborn babies has been collected, and a new minutiae descriptor based on deep neural network architecture has been proposed. Further, in [16], authors have provided a feasibility study for using toe prints to identify the children as they grow; it is difficult to capture the complete footprint from a regular fingerprint sensor. In this work, the authors have collected the toe print database of children varying from 4 years to 13 years of age and shown a feasibility analysis of toe print by considering the two standard fingerprint matching toolboxes.

There is no other work (to the best of our knowledge) that addresses the use of toe print for adults and persons with different abilities except [16] (this is for children). Especially, many of the people with different abilities are not able to provide their fingerprints as the biometric data for identification, and in these cases, a toe print can be one of the potential biometric traits. In this paper, a toe print database has been collected from different persons ranging from 17-64 years of age. Further, it is shown that the toe print is also feasible to be utilized as a potential biometric trait by comparing its performance with fingerprints over a standard fingerprint verification tool.

3. Experimental Analysis

This section includes the complete experimental analysis to show the feasibility of toe print as a probable biometric trait by comparing its performance with other fingerprints over a standard fingerprint verification method, i.e., Verifinger Demo [12]. The systematic analysis in a step-by-step manner has been discussed as follows.

3.1. Database description

Since the study on toe print has not been done in the past except for children ranging from 4-13 years of age [16], there is a need for a toe print database. This work presents a novel toe print database that has been collected from different persons ranging from 17-64 years of age, and the duration for collecting the database is around six months. The fingerprint sensor (Futronic FS60), which has been used, is an optical sensor with 500 ppi resolution, and this can capture all four impressions of a complete slap at a time and toe print. The acquisition of toe print using the Futronic FS60

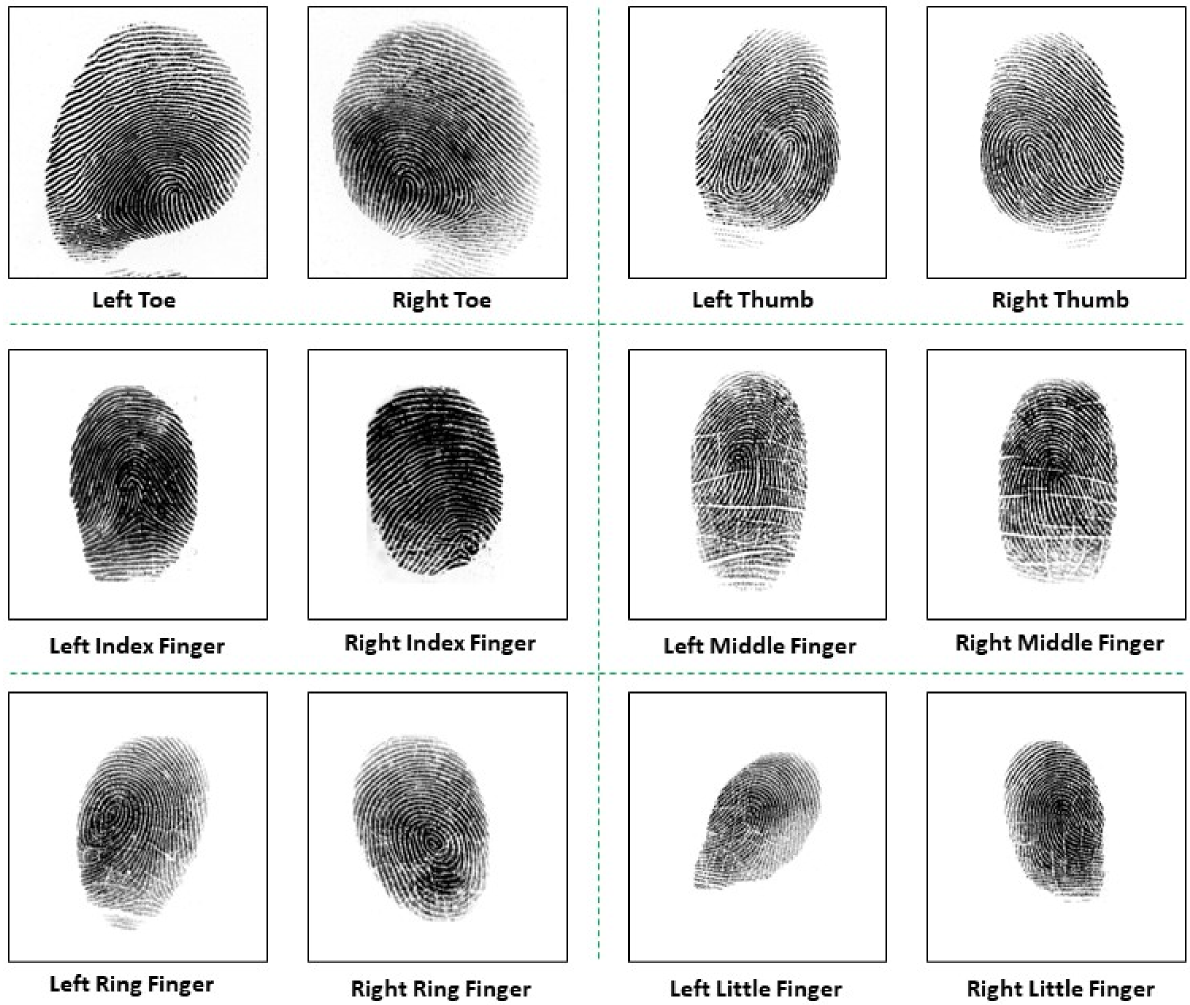


Figure 1: A few samples of the collected database with respect to the toe prints and the impressions of all the fingers of a person/subject

sensor has been depicted in Figure 3. There is a total of 100 persons from which the database has been collected, and the impressions of both toe print (big toe print) as well as all ten fingers are collected from each person. This database is made available in public domain via [14]. Thus, there are 10-10 samples for all types of impressions in the database for each subject, which makes a total of 120 samples for each person. As we know that the impressions that are taken from different fingers of the left and right hand, as well as toe print of the left and right foot of a person, are completely different from each other. Therefore, the database comprises 200 subjects by dividing the total samples into left and right hands as well as feet. This ends up giving the ten samples for each impression, i.e., toe print, thumb, index finger, middle finger, ring finger, and little finger for each subject as depicted in Table 1. The quality and dimension of the sample shown in the table are computed after cropping the raw images captured during the database collection. Further, this novel toe print database has been evaluated in terms of the performance of a biometric verification system by means of some performance metrics that are discussed in the next section.

3.2. Performance metrics

We have mainly utilized the three standard metrics to evaluate the performance of a biometric system based on toe print, then compared with the fingerprint impressions. First, False Acceptance Rate (FAR), which is a ratio between the number of imposters accepted as genuine users and the total number of imposter comparisons. Second, False Rejection Rate (FRR), which is a ratio between the number of genuine users rejected as an imposter and the total number of genuine comparisons. Third, Equal Error Rate (EER), which is a point where both FAR and FRR values become equal. So, performance is evaluated in terms of these aforementioned metrics. Further, in order to compute these metrics,

Table 1: A brief description of collected toe print database along with different fingerprint impression

Biometric trait	Sensor	Dimension	Quality	Number of samples (#subjects $\times$ #samples)
Toe print	Optical sensor	360×380	300 dpi	$200 \times 10 = 2000$
Thumb				
Index finger				
Middle finger				
Ring finger				
Little finger				

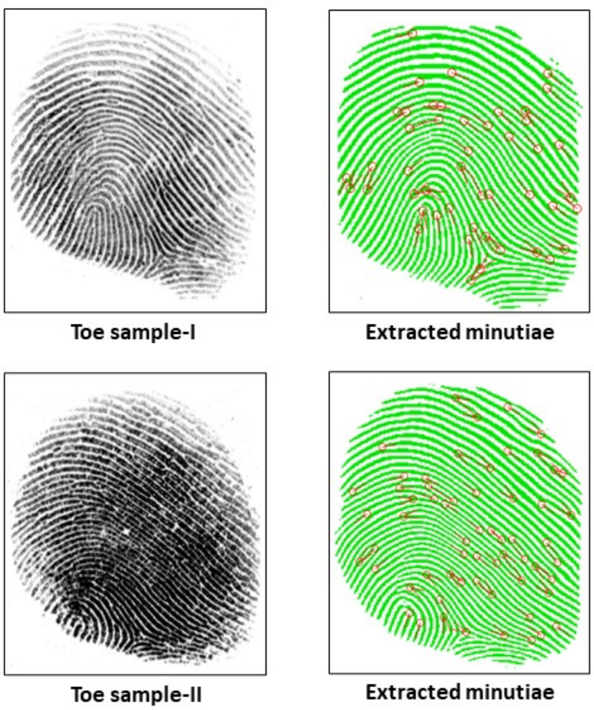


Figure 2: Representation of extracted minutiae using Verifinger Demo [12] corresponding to the given toe print sample-I and sample-II

Figure 3: Acquisition of toe print using Futronic FS60 optical fingerprint sensor

two standard fingerprint verification protocols [10] are used and discussed in the next section.

3.3. Evaluation protocols

The evaluation protocols, which have been used, are 1-versus-1 (1-vs-1) and Fingerprint Verification Competition (FVC) protocols. In the 1-vs-1 protocol, for each database, the first sample of each subject is enrolled and matched with the second sample of the same subject to compute the genuine scores, and finally computing FRR. Further, to compute the imposter scores and FAR, the first sample of each subject is enrolled and matched with the first samples of all the remaining subjects. In the FVC protocol, to compute the genuine scores and FRR, an exhaustive matching is performed compared to 1-vs-1, where each sample of a subject is enrolled and matched with all remaining samples of the same subject for a database (excluded the duplicate pairs). In addition, the approach similar to the 1-vs-1 protocol is utilized to compute the imposter scores and FAR value in the FVC protocol.

In our novel database, a total of six parts are there, i.e., toe print, thumb, index finger, middle finger, ring finger, and little finger. Each part of the database includes 200 subjects with ten samples for each subject that gets a total of 2000 samples in each part. Therefore, the total number of genuine comparisons in the 1-vs-1 and FVC protocols are 200 and $\frac{(10\times9)}{2} \times 200 = 9000$, respectively, to compute the genuine scores and FRR. To compute the imposter scores and FAR, the total number of imposter comparisons in both protocols are the same, which is equal to $\frac{(200\times199)}{2} = 19900$.

3.4. Performance analysis

The protocols discussed above are utilized to evaluate the performance in terms of FRR, FAR, and EER over the Verifinger Demo fingerprint verification tool. First, the genuine and imposter scores are computed following the 1-vs-1 and FVC protocols for toe print along with all remaining five parts of fingerprint databases. The values of FRR and FAR are computed using these scores while considering the ac-

Table 2: The percentage value of EER obtained for toe and different fingerprint impressions using standard fingerprint verification tool over both the matching protocol

Biometric trait	EER(%)	
	1-vs-1 protocol	FVC protocol
Toe print	0.04	0.01
Thumb	0.00	0.02
Index finger	0.00	0.24
Middle finger	0.59	0.34
Ring finger	0.01	0.54
Little finger	0.00	0.59

Table 3: The percentage value of Kolmogoro-Smirnov (KS) test obtained for toe and different fingerprint impressions using standard fingerprint verification tool over both the matching protocol

Biometric trait	KS-test value (%)	
	1-vs-1 protocol	FVC protocol
Toe print	99.94	99.98
Thumb	100	99.97
Index finger	100	99.70
Middle finger	99.40	99.52
Ring finger	99.99	99.26
Little finger	100	99.22

ceptance threshold varying from 0% to 100% with a step size of 0.01%. Further, these FRR and FAR values with respect to the different thresholds are plotted against the threshold values, and the point where the plots of FRR and FAR intersect gives the value of EER to the corresponding part of the database. The plots between the threshold and FAR / FRR for different six parts of the database are shown in Figure 4 considering both the evaluation protocols. Although Figure 4 shows the EER values for toe print and fingerprint databases, the exact values of EER are depicted in Table 2 for both the evaluation protocol. As it can be clearly seen in Table 2 that the toe print and all other parts of the database have attained the value of EER near to 0%. Moreover, the value of EER for toe print is clearly comparable with other values for fingerprint impressions and depicts the high discriminative nature for inter-class subjects and high similarity nature for intra-class samples. These EER values for a biometric system based on toe print are significantly good compared to fingerprints and can be considered as one of the potential biometric traits. In addition, to show the separability of score distributions, plots have been displayed in Figure 5 for all the six parts of the database. Further, to show the separability of genuine and imposter score distributions, statistical analysis has been presented in the next section using two different statistical hypothesis tests.

3.5. Statistical analysis

Two statistical hypothesis tests, i.e., Kolmogorov-Smirnov (KS) test [15] and t-test [17] are utilized to perform the statistical analysis of the computed genuine and imposter scores for different parts of our database. These hypothesis tests are basically used to show the significant difference between the genuine and imposter scores. Brief details about the KS-test and t-test are as follows.

3.5.1 Kolmogorov-Smirnov (KS) test

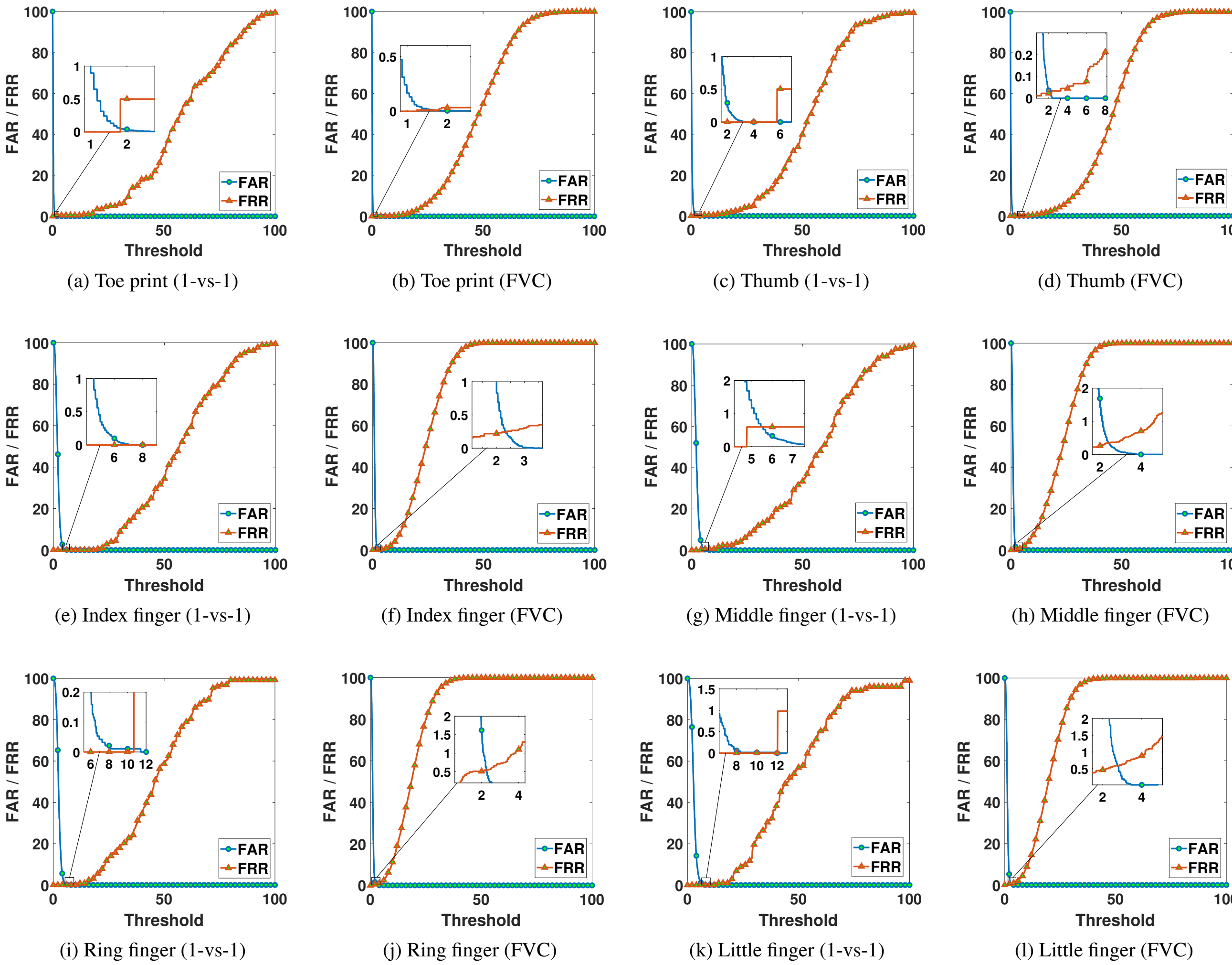
KS-test is a non-parametric test used to test the similarity between a sample and a reference probability distribution called one sample KS-test or between two different samples called a two-sample KS-test. In this paper, to analyze the difference between genuine and imposter scores, a two-sample KS-test has been used. The results of the KS-test, i.e., KS-stat comes between 0 and 1, and the value of KS-stat near 1 represents that the two input samples are significantly different from each other and vice-versa. The results of the KS-test on genuine and imposter scores computed for different parts of the database are given in Table 3 (the values are given in percentage). It can be clearly seen in Table 3 that the values are near to 100% for all the databases on both the protocol, and this means that the genuine and imposter scores are significantly different from each other.

3.5.2 T-test

The t-test is a statistical hypothesis test that is also used to show the significant difference between the two samples. In this paper, we have performed a two-sample unpaired t-test under the 5% significance level to show the significant difference between the genuine and imposter score distributions. The results of the t-test for toe print and other fingerprints are shown in Table 4. It is well-established from the Table 4 that the absolute value of $t - stat$ (obtained value for input score distributions) is greater than the value of $t - critical$ (standard values to reject or accept null hypothesis) for all the databases. This condition represents that the null hypothesis has been rejected, and the given input genuine and imposter score distributions are significantly different from each other.

4. Conclusion and Future Work

The fingerprint is one of the biometric traits which has been widely used to verify the identity of a person. However, in some of the cases, such as for infants and toddlers, the footprint has been used, which further becomes difficult to capture as the age of infants and toddlers grow. Hence, the study on the use of toe print instead of footprint has been discussed in the literature. Nevertheless, the study on the use of toe print as a potential biometric for a nor-



(a) Toe print (1-vs-1)
(b) Toe print (FVC)
(c) Thumb (1-vs-1)
(d) Thumb (FVC)
(e) Index finger (1-vs-1)
(f) Index finger (FVC)
(g) Middle finger (1-vs-1)
(h) Middle finger (FVC)
(i) Ring finger (1-vs-1)
(j) Ring finger (FVC)
(k) Little finger (1-vs-1)
(l) Little finger (FVC)

Figure 4: Plots that are depicting the EER point and change in values of FAR and FRR while varying the threshold value for toe print along with different fingers in the case of 1-vs-1 and FVC protocol

Table 4: Results of t-test obtained for toe and different fingerprint impressions using standard fingerprint verification tool over both the matching protocol

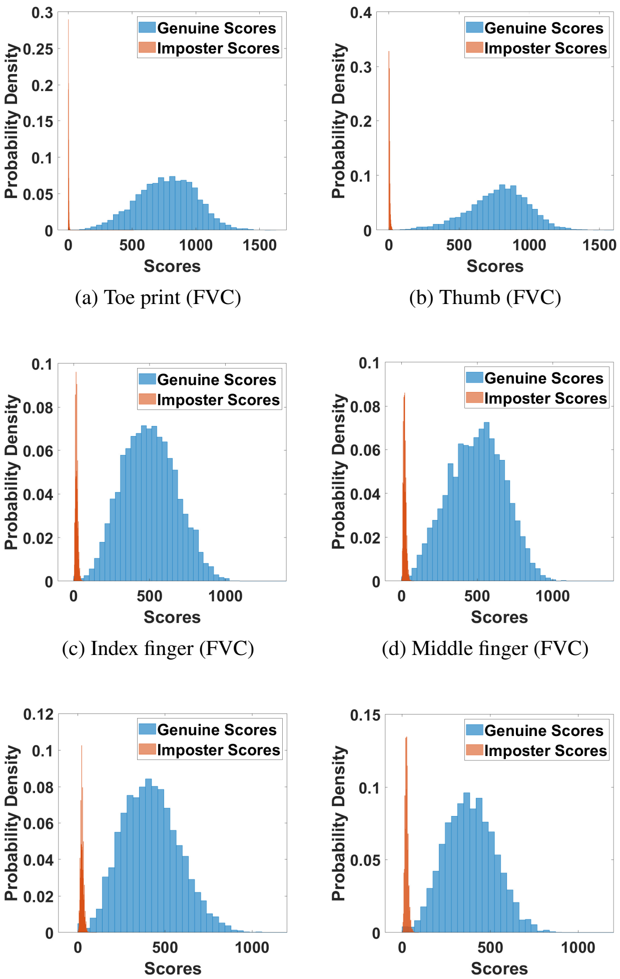
Biometric trait	1-vs-1		FVC		$\|t_s\| > t_c$
	t_s	t_c	t_s	t_c	
Toe print	42.6	1.97	315.5	1.96	True
Thumb	46.4	1.97	348.6	1.96	True
Index finger	40.5	1.97	244.8	1.96	True
Middle finger	35.9	1.97	225.5	1.96	True
Ring finger	30.1	1.98	178.9	1.96	True
Little finger	24.3	1.98	171.4	1.96	True

$t_s : t - stat$ and $t_c : t - critical$

mal person and person with different abilities has not been done in the past. In this paper, a feasibility study of the toe print as a biometric trait has been presented by using a novel toe print database, which is collected from different persons of age varying from 17-64 years. A biometric system (Verifinger Demo) based on a novel toe print database has been evaluated in terms of performance and compared with fingerprints. The results show that the toe print can be utilized as one of the potential biometric traits to verify a person's identity, especially for a person with different abilities. In addition, toe print improves the secrecy of the biometric data of a person as feet of a person are mostly covered, unlike fingerprints.

There are several interesting and important future directions which can be pursued further.

- In this analysis, an optical sensor has been used to collect toe prints data. This work can be further extended



(a) Toe print (FVC) (b) Thumb (FVC)

(c) Index finger (FVC) (d) Middle finger (FVC)

(e) Ring finger (FVC) (f) Little finger (FVC)

Figure 5: Plots that are depicting the genuine and imposter score distributions for toe print along with different fingers in the case of FVC protocol

by collecting the toe print data using a variety of sensors, such as capacitive, optical, ultrasonic, and thermal, to introduce variations in the quality of toe print images and enhance database sensor interoperability.

- It will be interesting to investigate the use of 3D toe prints in human recognition as contactless 3D fingerprints have been shown to be superior to 2D fingerprints in [1].

- Efforts can be made in developing the minutiae descriptors and the verification techniques for the toe print images, as well as combining fingerprint and toe print for multi-modal biometrics (as both can be captured from the same sensor).

- Similar to fingerprints, toe print-based authentication systems can be vulnerable to a number of attacks [2, 5, 11]. Development of techniques to counteract them can be taken up in future studies.

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