A Feasibility Study on Utilizing Toe Prints for Biometric Verification of Children

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Abstract

Biometric recognition allows a person to be identified by comparing feature vectors derived from a person's physiological characteristics. Recognition is dependent on the permanence of the biometric characteristics over long periods of time. There was been limited work evaluating the footprint as a potential biometric. This paper presents a longitudinal study of toe prints in children to understand if this biometric modality could be used reliably as a child grows. Data was collected and analyzed in children ages 4-13 years over five visits, spaced approximately six months apart, giving two years of data. This is the first footprint collection spanning this broad age range in children. Footprints were segmented into separate toe prints to examine whether current fingerprint recognition technology can provide accurate results on toe prints. Data was analyzed using two available fingerprint matchers, Verifinger and Bozorth3 from NIST Biometric Image Software (NBIS). Verifinger provides the best verification match scores using the toe prints, especially when using the hallux, the large toe. The hallux toe on Verifinger provides verification rates of 0% FAR and FRR for images collected on the same day and a FRR of 6.44% at a 1% FAR after two years have passed between collections. Additional longitudinal data is being collected to further these results.

1. Introduction

A standard practice is to collect the footprint image of a newborn baby. This provides a biometric marker for the child at birth for identification. However as children grow, their footprints grow beyond the size of what a standard sensor can capture. Due to this, you may capture less and less of the actual footprint as the child ages. However, toe prints stay inside of the capture range of sensors and possess ridges and valleys that make them strongly similar to fingerprints. The toe prints have patterns similar to fingerprints and contain minutiae points. Using the toe prints themselves can provide recognition with a basis that goes back to birth and is already being collected by hospitals. This paper proposes a preliminary study on the use of toe prints for recognition using already developed fingerprint algorithms.

The goal of this research is to understand the feasibility of using toe prints for biometric recognition in children to facilitate future research in the field. This paper will showcase three different experiments to examine this possibility and discuss future research steps.

2. Background

Even though infant footprints have been captured for many years, the use of footprint for automated biometric recognition is a relatively new research topic. Eryun Liu conducted research into infant recognition in 2017 examining 54 subjects over three collections from 2 days to 6 months old and saw reasonable recognition rates in footprint recognition during this time [5]. Nakajima et al. looks at ten volunteers and found a recognition rate of 30.45. This research was done by using an input pair of raw footprints that are normalized in direction and position [6].

Limited research has been done in the field of aging biometrics in children. Studies have been done on the effect of growth on fingerprints. When examining adolescents, it was found by Gottschilich et al. that modeling the growth of fingerprints improves matching [2]. This was done by examining the stability of the line patterns structure. While another study by UltraScan determined that the pattern of a fingerprint is developed and finalized by 24 weeks [8]. Other research examined fingerprint recognition over a one year period in children from age 0 to age 5 [3]. Beslay et al has also delved deeper into fingerprint aging and studied both children and the elderly [1]. This research helped show that fingerprint recognition in children is feasible and that models can be used to adjust for finger growth.

3. Experiment

Researchers were able to work with a local elementary school to recruit participants for this study. Thus far, five collection events have been held. Each of these collections are separated by approximately six months. During each of these collections six modalities were acquired. This paper will focus on the subjects' footprint. This paper investigates two main issues. The first is if a footprint is viable as a biometric to identify people. The second is the stability of match scores over time for a subject's footprint given up to two years of data.

3.1. Subject Enrollment

This study was approved by university Institutional Review Board (IRB) for studies involving human subjects. A parent was required to sign an informed consent document and the child was required to give an age-tiered assent, ranging from verbal to signed consent. A unique subject number was assigned to each student that is correlated with a bar code that each subject wore around their wrist during each collection.

3.2. Dataset

The footprint portion of the child biometric dataset that is analyzed in this paper was collected using the CertaScan Technologies child footprint sensor.

During collection, the children were asked to take their socks and shoes off a few minutes before their footprint is collected. This allows their feet to cool down and helps eliminate water or sweat halos around their toes. Since the youngest children are age 4, children were asked to place their five toes and balls of their feet on the scanner. The arch and back of the foot was typically not imaged. The child was instructed to stay still to ensure that all five toes are be recorded. When the footprint was of sufficient quality, the collector captured an image and continued on to the next foot.

For each collection, the process was repeated. This means that four footprints were taken in total, two of the right foot and two of the left foot. Due to the difficulty of collecting biometric data with children, not all toes were captured in every image. In total there are 177 subjects, ages 4 to 13, in the dataset spanning from one to five collections each. Table 1 below showcases the total number of subjects as well as the number of subjects with a single visit through five visits. It also shows the total number of toe print images in the complete dataset. The 18 subjects who only had a single visit of data were removed from data analysis as they do not provide any benefit for examining match scores over time.

3.3. Biometric Recognition Software

The toe prints were analyzed using two software programs designed for fingerprint matching. The first was the bozorth3 algorithm available in the NIST Biometric Imaging Software (NBIS) from US National Institute of Standards and Technology (NIST) [4]. Other NBIS software was used to convert the toe prints to WSQ image files and extract the minutiae information for the input into bozorth3. Bozorth3 computes match scores for two fingerprint images using fingerprint minutiae files computed using the mindtct algorithm available through NBIS.

The second software used was Verifinger by Neurotechnology [7]. Verifinger generates match scores from created fingerprint templates. JPG images are supplied to the software and converted to templates and matched to generate scores.

3.4. Example

Below is an example of a subject's biometric data taken from all five collections. Figure 1 shows one pair of footprints for each collection for one subject. It should be noted that there are two sets of footprints taken during each collection.

In order to utilize Verifinger and NBIS, the data had to be altered to fit inside the desired parameters of the software. To do this each footprint was segmented into five images, one for each toe. This allowed the software to treat the two prints as fingerprints. An example of the segmented footprint is shown in Figure 2 below.

4. Data Analysis

The data analysis is broken down into multiple sections. The first examines the scores generated by NBIS. The second is the analysis of the scores generated by Verifinger. The last section provides a further analysis of the scores, exploring the error rates by toe to determine which are more viable for use over others. The gallery was generated using the first toe images from a subject's first collection. The first collection is not necessarily the first collection of the study, but an individual subject's first collection, as subjects were added to the study as time progressed. Results will be presented in relation to each subject's first collection and be shown with the following abbreviations; A - first collection, B - second collection, C - third collection, D - fourth collection, E - fifth collection. Future notation will use AA to represent first collection to first collection, AB as first collection to second collection, and so on. Imposter matches were generated using each of the gallery images and choosing the same toe from random other subjects.

Total Subjects	1 Visit	2 Visits	3 Visits	4 Visits	5 Visits	Total Images
177	18	2	9	18	130	12923

Table 1: Subjects by visit and total toe print images

Figure 1: An example of the same subjects footprint. The images age from top to bottom starting with the top images at collection 1 (0 mos), collection 2 (6 mos from the first collection), collection 3 (12 mos), collection 4 (18 mos), and the bottom from collection 5 (24 mos).

4.1. NBIS analysis

For NBIS there were a total of 11774 genuine matches and 12017 imposter matches generated. Imposter matches are more evenly distributed among the different visits, however genuine matches are more skewed towards two and three visits. The genuine match distribution has 260 AA matches, 3103 AB matches, 3075 AC matches, 2766 AD matches, and 2570 AE matches. In comparison, the imposter match distribution is, 1881 AA matches, 2716 AB matches, 2736 AC matches, 2447 AD matches, and 2237 AE matches. There is a distinct difference between the average match rate for the genuine match scores and the imposter match scores for each visit type. The average match scores as well as the 95% confidence interval for the average match score is displayed in table 2. While the average match scores are separated, that separation is small given the bozorth3 algorithm has generated scores over 200. As the error rates will showcase, this contributed heavily to the high error rates from the bozorth3 algorithm.

Figure 2: An example of segmented toe prints from one foot

The equal error rate and the FRR at 1% FAR are shown in table 3. The equal error rate saw a general increase as time progressed from same day to two years. As you might expect, the bozorth3 algorithm was not capable of working with toe print images as well as fingerprints. The detection error tradeoff for the bozorth3 algorithm is shown in figure 3.

4.2. Verifinger analysis

Verifinger has fewer matches than NBIS algorithm, Verifinger does not perform matching on poor quality images. Due to child biometrics being difficult to collect, not all toes were able to be clearly collected and Verifinger rejected a portion of the images. There are a total of 10510 genuine matches and 10626 imposter matches. This genuine matches consisted of 242 AA matches, 2742 AB

Match Type	Collection	Number of Matches	Average Match Score	95% C.I. of Average Match Score (+-)
Genuine	AA	260	38.9	5.98
Imposter	AA	1881	8.6	0.25
Genuine	AB	3103	19	0.75
Imposter	AB	2716	8	0.19
Genuine	AC	3075	18.5	0.75
Imposter	AC	2736	7.8	0.18
Genuine	AD	2766	17.7	0.7
Imposter	AD	2447	8	0.19
Genuine	AE	2570	14.9	0.56
Imposter	AE	2237	7.7	0.2

Table 2: Average match scores for NBIS matcher

Collection	Equal Error Rate%	FRR at 1% FAR
AA	29.23	62.5
AB	36.4	76.5
AC	36.2	73.75
AD	37.1	77.4
AE	38.4	82.2

Table 3: Error rates on NBIS matcher

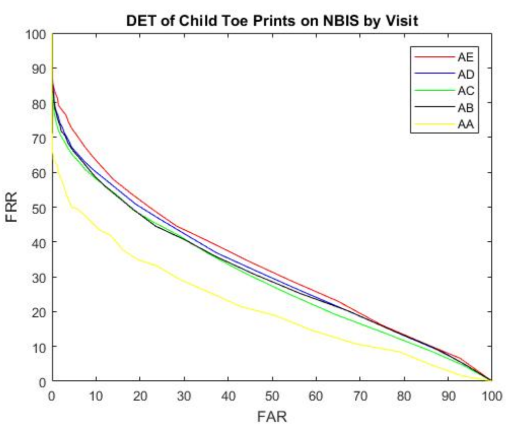

Figure 3: Detection error tradeoff for toe prints on NBIS by visits

matches, 2751 AC matches, 2513 AD matches, and 2262 AE matches. The imposter matches are comprised of 1603 AA matches, 2411 AB matches, 2446 AC matches, 2191 AD matches, and 1975 AE matches. Unlike with NBIS, the distinction between the average match scores of the genuine and imposter matches have a gap. The average matches scores and 95% confidence interval for the averages are shown in Table 4. With the Verifinger results we see that the average match score for genuine is decreasing over time, with imposter match scores staying generally consistent across visits. This gap between the average match scores of the genuine and imposter matches does provide some validity to Verifinger being able to process toe prints similar to fingerprints.

The equal error rates for the Verifinger matcher show a stark difference from what is displayed by NBIS. The equal error rates and FRR at 1% FAR are shown in Table 5. As anticipated with the decrease of the average genuine match score, the equal error rate increased as the time difference between samples increased. The detection error tradeoff for the Verifinger algorithm is shown in Figure 4.

4.3. Verifinger Hallux Analysis

While Verifinger results are promising, delving deeper into the data shows where the successes and failures of the algorithm are occurring. By separating the data by individual toe, the toes that provide the best results can be isolated. After dividing the data by individual toes it was found that the hallux, or big toe, provided the best results for matching. This is not surprising as the hallux is the largest toe and easiest for the subject to press flat on the collection sensor. The other toes can appear closer to partial prints when collected, however the hallux looks similar to a fingerprint. Being a subset of the Verifinger data, the number of matches is considerably smaller for the hallux. There are 2320 gen-

Match Type	Collection	Number of Matches	Average Match Score	95% C.I. of Average Match Score (+-)
Genuine	AA	242	269.3	23.96
Imposter	AA	1603	14.4	0.44
Genuine	AB	2742	150.7	4.48
Imposter	AB	2411	12.4	0.33
Genuine	AC	2751	139.7	4.1
Imposter	AC	2446	12.49	0.33
Genuine	AD	2513	129.8	3.93
Imposter	AD	2191	12	0.33
Genuine	AE	2262	109.6	3.6
Imposter	AE	1975	12.2	0.35

Table 4: Average match scores for Verifinger matcher

Collection	Equal Error Rate%	FRR at 1% FAR
AA	6.6	8.3
AB	10.4	16.9
AC	11.5	18.6
AD	12.25	18.9
AE	12.8	21.9

Table 5: Error rates on Verifinger matcher

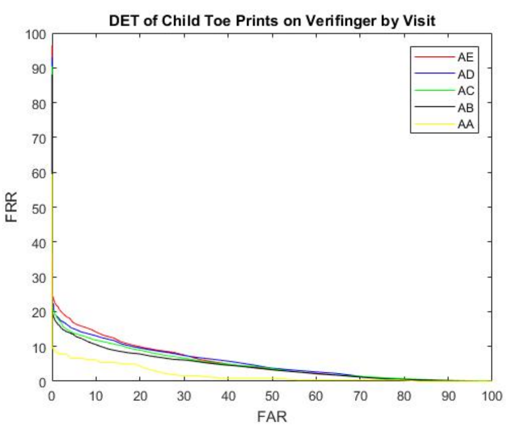

Figure 4: Detection error tradeoff for toe prints on Verifinger by visits

uine matches and 2367 imposter matches for the hallux. The genuine matches consist of 52 AA matches, 612 AB matches, 601 AC matches, 547 AD matches, and 508 AE matches. While the imposter matches are comprised of 344 AA matches, 529 AB matches, 534 AC matches, 503 AD matches, and 457 AE matches. The average match score and the 95% confidence interval for the average are shown in Table 6.

When examining just the hallux the error rates drop considerably further. For same day matches, there was a 0% EER and the highest was 3.95% for AD matches. All of the equal error rates as well as the FRR at 1% FAR are shown in Table 7. This gives the best overall results from any toes. The error rates for each toe type are shown in Figure 5. The hallux (T1) has far and away the lowest errors, whereas all of the other toes were similar in error rates. The DET for the hallux across visits is displayed in Figure 6.

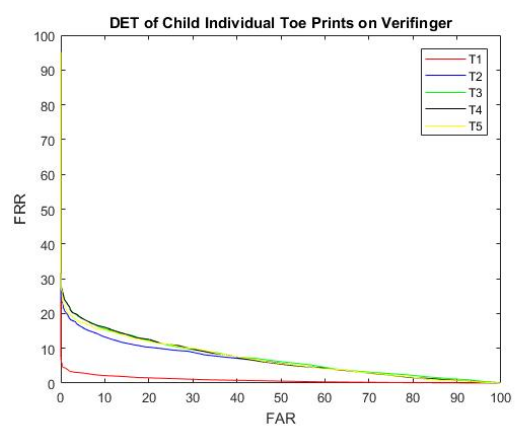

Figure 5: Detection Error Tradeoff for separated by each toe type on Verifinger

Match Type	Collection	Number of Matches	Average Match Score	95% C.I. of Average Match Score (+-)
Genuine	AA	52	479.9	59.29
Imposter	AA	344	6	0.38
Genuine	AB	612	231.5	11.41
Imposter	AB	529	4.7	0.3
Genuine	AC	601	211.8	10.31
Imposter	AC	534	4.7	0.25
Genuine	AD	547	190.5	9.77
Imposter	AD	503	4.8	0.29
Genuine	AE	508	150.1	8.39
Imposter	AE	457	5	0.34

Table 6: Average match scores for hallux toe print for Verifinger matcher

Collection	Equal Error Rate%	FRR at 1% FAR
AA	0	0
AB	2.78	3.33
AC	2.6	3.27
AD	3.95	4.94
AE	3.55	6.44

Table 7: Error Rates for hallux toe prints on Verifinger matcher

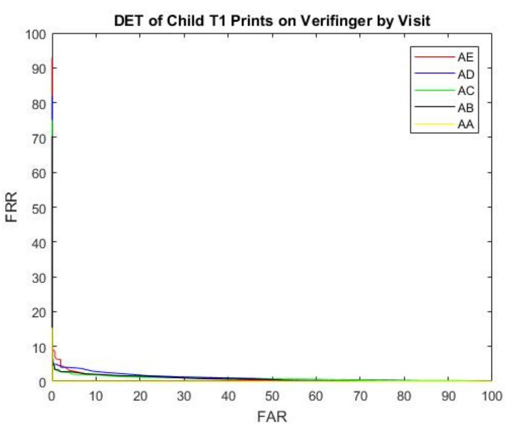

Figure 6: Detection Error Tradeoff for hallux toe prints on Verifinger by visits

5. Conclusion and Future Work

The results show promise on the premise of using toe prints can be used for biometric recognition in children. Having an algorithm that performs well without adapting to the toe print recognition shows room for further research. Additional data is being collected which will be used for future expanded work. Future work will explore models of growth to further improve performance. Additionally, methods to fuse the toe prints will be examined for possible improvements in the recognition rate. In our future work we also aim to design a Convolutional Neural Network (CNN) based minutia and pore feature extractors for toe prints. CNN based systems have shown promising improvement in current fingerprint systems which makes them a possible candidate for an accurate identification system based on the toe prints.

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