Fingerprint Recognition of Young Children

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***Abstract*—In 1899, Galton first captured ink-on-paper fingerprints of a single child from birth until the age of 4.5 years, manually compared the prints, and concluded that "the print of a child at the age of 2.5 years would serve to identify him ever after". Since then, ink-on-paper fingerprinting and manual comparison methods have been superseded by digital capture and automatic fingerprint comparison techniques, but only a few feasibility studies on child fingerprint recognition have been conducted. Here, we present the first systematic and rigorous longitudinal study that addresses the following questions: (i) Do fingerprints of young children possess the salient features required to uniquely recognize a child? (ii) If so, at what age can a child's fingerprints be captured with sufficient fidelity for recognition? For our study, we collected fingerprints of 309 children (0-5 years old) four different times over a one year period. We show, for the first time, that fingerprints acquired from a child as young as 6 hours old exhibit distinguishing features necessary for recognition, and that state-of-the-art fingerprint technology achieves high recognition accuracy (98.9% true accept rate at 0.1% false accept rate) for children older than 6 months. Further, using mixed-effects statistical models, we show that the recognition accuracy is not significantly affected over the one year time lapse in our data. Given rapidly growing requirements to recognize children for vaccination tracking, delivery of supplementary food, and national identification documents, our study demonstrates that fingerprint recognition of young children (6 months and older) is a viable solution based on available capture and recognition technology.**

***Index Terms*—child identity, child fingerprint recognition, identity for lifetime, biometrics for social good**

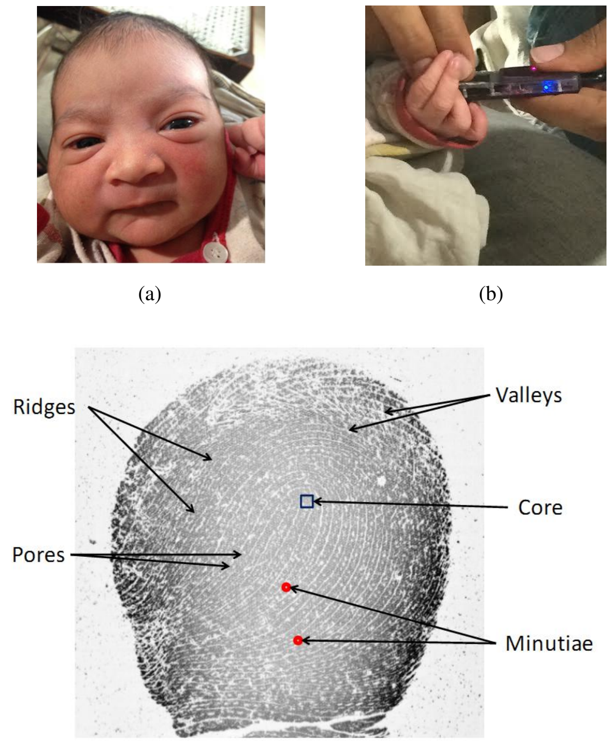

Fig. 1. Fingerprint capture of a 6 hours old child using the custom 1,270 ppi fingerprint reader designed by NEC [3]. (a) Face image of the child, (b) the fingerprint capture process, and (c) the captured left thumb print image with annotated features (ridges and valleys, core, minutiae, and pores).

I. Introduction

> *"Let no one despise the ridges on account of their smallness, for they are in some respects the most important of all anthropological data . . . They have the unique merit of retaining their peculiarities unchanged throughout life, and afford in consequence an incomparably surer criterion of identity than any other bodily feature."*
> - Galton [2]

GALTON first explored the feasibility of using fingerprints for identifying young children in the year 1899 [4]. He obtained inked fingerprint impressions of a newborn from birth until 4.5 years of age, manually compared them, and conjectured that it was possible to use fingerprints to recognize children older than 2.5 years of age. Since Galton's study on fingerprinting young children, there have been significant advances in digital capture and automatic comparison of fingerprints. The ink-on-paper fingerprint acquisition process has been mostly superseded by *live scan* methods, which directly provide a digital fingerprint image. Tedious manual comparison of fingerprints has been replaced by fast and robust automatic comparison methods. These technological advancements, as well as emerging applications that require recognition of children, have reignited the interest of the fingerprint research community in investigating child fingerprinting, and have recently led to a few feasibility studies [5] [6] [7] [8]. However, the consensus among fingerprint practitioners and the general public is that it is not feasible to recognize young children[1] using their fingerprints.

Biological evidence, on the other hand, suggests that fingerprints are fully formed by the sixth month of fetal life and are physiologically present on human fingers at birth [9]

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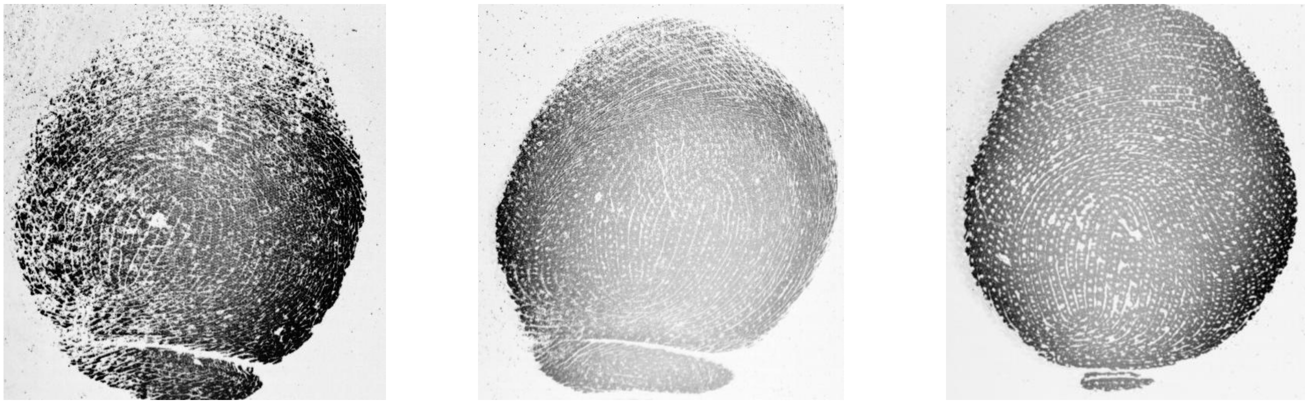
[1]The terms *child* and *children*, in this paper, refer to a child in the age range of 0-5 years.



(a) (b) (c)

Fig. 2. Left thumb print images of the same child captured at three different ages: (a) 1 day, (b) 3 months and (c) 6 months using the custom 1,270 ppi reader designed by NEC [3].

[10] [11]. Further, it is also premised that fingerprints are (i) *unique*, i.e., no two fingers, even of the same individual, have identical patterns, and (ii) *persistent*, i.e., they do not change over the lifetime of an individual [12] [2]. Whereas uniqueness and persistence of fingerprints have been investigated for adult fingerprints [13] [14] [15] [16] [17] [18], there has been, to our knowledge, no systematic and rigorous longitudinal study to address the following fundamental questions pertaining to child fingerprints:

1) Do child fingerprints possess the salient characteristics necessary to uniquely recognize a child?
2) What is the youngest age at which a child's fingerprints can be captured with sufficient fidelity to uniquely recognize the child?

The objective of this study is to address the aforementioned questions by:

- collecting a longitudinal database of child fingerprints using both a commercial-off-the-shelf 500 ppi reader and a custom 1,270 ppi reader,
- evaluating the recognition performance of a state-of-the-art Automated Fingerprint Identification System (AFIS) on child fingerprints, and
- investigating the persistence of genuine scores from child fingerprints using mixed-effects statistical models.

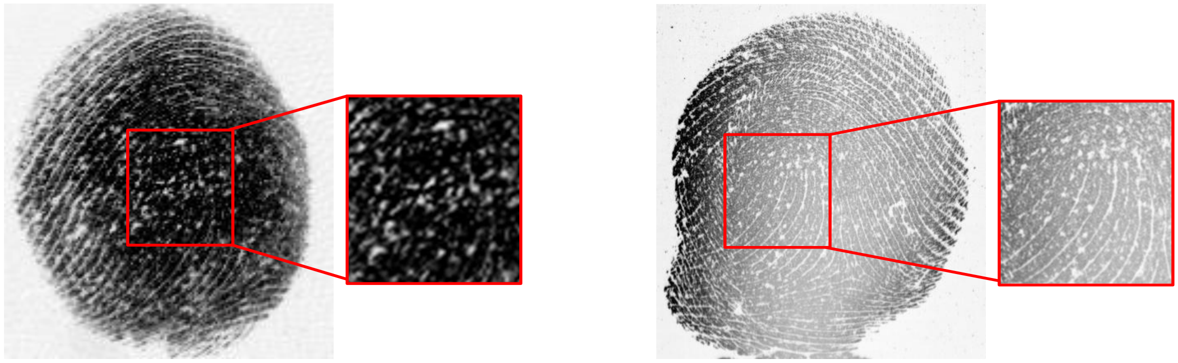
In an earlier study [19], we investigated the feasibility of capturing and recognizing fingerprints of young children using an off-the-shelf 500 ppi fingerprint reader. However, due to lack of longitudinal data in that study, we were not able to assess the utility of fingerprints for recognizing children over time. To acquire longitudinal fingerprint data of children, we initiated a data collection effort at the Saran Ashram hospital in Dayalbagh, India. We captured the left and right thumb impressions of 309 children (ranging in age from 0-5 years) in four different sessions (March 2015, September 2015, January 2016 and March 2016) over a period of one year.

We show, for the first time, that it is indeed feasible to capture fingerprints of children, even as young as 6 hours old, using a custom high-resolution (1,270 ppi) and compact (7.2 cm $\times$ 3.5 cm $\times$ 7.5 mm) fingerprint reader (see Fig. 1). Experimental evaluation conducted on the longitudinal fingerprint images using a state-of-the-art AFIS[2] shows that (i) 500 ppi fingerprints suffice for recognizing children older than 12 months at the time of enrolment (TAR of 99.5% at FAR of 0.1%), and (ii) 1,270 ppi prints are necessary for recognizing children at least 6 months of age at enrolment (TAR of 98.9% at FAR of 0.1%). Further, using mixed-effects statistical models, we show that child fingerprint recognition accuracy is not significantly affected over the one-year time period in our study.

At present, there are over 600 million children worldwide that are between 0-5 years old [21], and an average of 353,000 newborns are added to this population every day [22]. Given that a majority of these childbirths occur in developing countries where children do not have any form of identification, there is an increasing demand for child recognition in a number of different applications. Examples of such applications include:

- *Vaccination tracking of children*, especially in the least developed countries, where over 5 million children die every year due to vaccine-preventable diseases [23], and vaccine wastage rates are reported to be as high as 50 percent[3]. Several governmental and non-governmental health organizations have initiated routine vaccination programs in these countries (e.g. VaxTrac in Benin and Nepal[2]) to improve vaccination coverage.
- *Improving child nutrition*, particularly in the least developed countries, e.g, Bangladesh, where "almost one in two children under the age of 5 years are chronically undernourished (stunted) and 14 percent suffer from acute undernutrition". Initiatives are being taken by the World Food Programme to provide "fortified supplementary food to children between 6-59 months of age suffering from moderate acute undernutrition until they recover"[4].
- *National ID programs*, such as Aadhaar [24], which aim to provide a unique identity beginning at birth to every

[2]We cannot disclose the AFIS vendor name due to our licensing agreement.
[3]http://vaxtrac.com
[4]https://www.wfp.org/sites/default/files/IMCN%20factsheet.pdf



(a) (b)

Fig. 3. Fingerprint images of the left thumb of a 6 weeks old child captured using the two fingerprint readers used in this study, (a) the 500 ppi Digital Persona U.are.U 4500 HD fingerprint reader [20] and (b) the 1,270 ppi custom fingerprint reader designed by NEC [3]. Fingerprint regions marked in the red square have been enlarged to show the ridge details. The 1,270 ppi reader is able to better capture the minute details present on a child's finger (e.g. ridge endings and bifurcations) compared to the 500 ppi reader.

resident of a country, and use biometric identifiers (e.g. fingerprints and iris) for this purpose.

- *Giving children an identity for lifetime* by developing digital identity systems using fingerprints; such systems can benefit "children and people at risk from human trafficking, refugee crisis situation, and lack of access to basic services"[5].

Our findings support the use of fingerprint recognition as a viable solution for recognizing children in such emerging applications.

The major differences between our preliminary work [1] and this paper are as follows:

- An in-depth review of child fingerprint recognition studies since Galton's first investigation in the year 1899.
- Collection of fingerprints of 309 children (age range: 0-5 years) in four different sessions over a one year period. For our preliminary work [1], we had collected fingerprints of only 66 children in the 0-6 months old age group in two different sessions 2-4 days apart.
- Systematic and rigorous performance evaluation of child fingerprint recognition accuracy over the one year period. We show that state-of-the-art fingerprint recognition capture and recognition technology offers a viable solution for recognizing children older than 6 months (98.9% TAR at 0.1% FAR).
- Use of mixed-effects statistical models to study the trend of genuine fingerprint similarity scores over the one year time period. We show that child fingerprint recognition accuracy does not degrade over the one year time lapse in our data.

II. Background

In 1880, Faulds [12] first advocated the use of fingerprints as a means of personal identification, and suggested that fingerprints are persistent and can be used to uniquely identify individuals. Thereafter, in 1883, Kollman studied the formation of dermatoglyphic ridge patterns present on our hands and feet [25]. He stated that the ridge patterns become perceptible to a certain extent in the fourth month of gestation and are fully formed by the sixth month of fetal life. Subsequently, Cummins and Midlo [9] in 1961, and, Penrose and Ohara [10] in 1973, validated the finding that ridge patterns are physiologically present on our fingers at birth. The seminal work of Galton [2] introduced the use of minutiae points (minute details present in fingerprints, mostly as ridge endings and ridge bifurcations) for fingerprint recognition (comparison), and corroborated the claims of uniqueness and persistence of fingerprints for adults[6]. However, the fundamental questions pertaining to (i) whether fingerprints can be captured for children, and (ii) if so, at what age fingerprints of children attain the same fidelity for recognition as that of adults, were not addressed.

Driven by the quest to answer questions regarding child fingerprints, almost 120 years back in 1899, Galton obtained inked fingerprint impressions of all ten fingers of a single child, captured initially every few days and subsequently every few months, from birth until she was 4.5 years old [4]. He compiled six sets of all ten fingerprints captured at the following age intervals: (i) 9 days-1 month, (ii) 1 month-6 weeks, (iii) 5-7 months, (iv) 17 months, (v) 2.5 years, and (vi) 4.5 years. From each set, Galton selected the best quality finger impressions and summarized his key observations pertaining to child fingerprints as follows [4].

- *"Far more delicate printing is needed on account of the low relief of features and minuteness of the pattern."*
- *"Babies are the most difficult to deal with, the persistent closing of their fists being not the least of the difficulties."*
- *"Many undecipherable blurs are made before one moderate success is attained, and at best, the print is made by a mere dab of the finger, rolled impressions being practically impossible."*
- *"First four sets are more or less blotted, and do not show more than a small part of the surface which is desirable to print."*

[5] http://id2020.org/.

[6] The claims of uniqueness and persistence of fingerprints have since been scientifically validated by Pankanti *et al.* [14], and Yoon and Jain [18].

(a)

(b)

Fig. 4. Fingerprint data collection at the Saran Ashram hospital in Dayalbagh, India. (a) Parents signing the consent form permitting us to capture their child's fingerprints, and (b) data capture at the two data collection stations in Dr. Bhatnagar's office.

- *"Fifth and sixth sets are clear though pale, for it was necessary to spread the ink very lightly to avoid blots."*

Galton further stated that *"the fifth and sixth sets of prints"* captured at 2.5 and 4 years, respectively, *"showed the same order of complexity that is found in the ridges of an adult"* and were *"perfectly suited for comparisons"*. Based on these observations, he inferred that *"the print of a child at the age of 2.5 years would serve to identify him ever after"*. However, it should be pointed out that Galton made these conclusions based on fingerprints captured from a single child using the *ink-on-paper* process. Since then, only a few feasibility studies have been conducted to investigate child fingerprinting. These are summarized below.

- In 2004, the Netherlands Organization for Applied Scientific Research (TNO) conducted a study [5] to assess the viability of using biometric traits for Dutch travel documents. They concluded that *"it was not possible to obtain clear fingerprints from children under 4 years of age"* due to minuteness of the ridge pattern on their fingers.
- A pilot project "Biometrics Data Experimented in Visas (BIODEV II)" was initiated in 2007 by eight European member states for capture, storage and verification of biometric data for Schengen visa applicants [6]. Based on fingerprints of 300 children captured in Damascus (Syria) and Ulan Bator (Mongolia), the study concluded that it is challenging to acquire fingerprints of children below 12 years of age.
- Between 2006-2009, Ultra-Scan, a fingerprint vendor specializing in ultrasound-based readers, conducted a study [7] to model the growth of fingerprint patterns of children through adolescence. But, it did not provide any insights into child fingerprint capture and recognition.
- In 2013, the Joint Research Center of the European Commission published a technical report [8] on fingerprinting of children. The study was based on fingerprints of 2,611 children (0-12 years old) collected using 500 ppi fingerprint readers during passport processing by the Portuguese government. The report concluded that fingerprint recognition of children younger than 6 years of age is difficult.

In summary, as previously mentioned, the prevailing belief in the fingerprint and user community is that (i) reliable capture of fingerprints of children younger than 2 years is not feasible, and (ii) fingerprint-based recognition of young children cannot be accomplished. The study presented here contradicts this general belief by showing that it is indeed feasible to capture child fingerprints with sufficient fidelity to recognize children older than 6 months with reasonable accuracy (TAR of 98.9% at FAR of 0.1%) using a custom 1,270 ppi fingerprint reader.

III. Longitudinal Child Fingerprint Capture

To investigate child fingerprint capture and recognition, a longitudinal data collection effort was initiated at the Saran Ashram hospital in Dayalbagh, India, with the aim of fingerprinting the same children in four different sessions (March 2015, September 2015, January 2016 and March 2016) over a one year period. Data was captured in a pediatrician's (Dr. Anjoo Bhatnagar) office while she was examining her patients. Two data capture stations, each manned by the authors, were set up for capturing fingerprint data. Face images of the children were also captured using the 8 MP rear camera of iPhone 5/5s. In addition, the child's name, age, gender, and address, and contact number of the child's parents were noted to contact the parents for follow-up visits during subsequent data collection sessions.

Fig. 4 shows the data collection process. Parents were required to sign a consent form (approved by the Michigan State University's institutional review board and the ethics committee of the Saran Ashram hospital) giving their consent to provide their child's fingerprint and face images. Fingerprint and face images were captured at one of the two data collection stations, and an incentive (a bag of staple food, voucher for the local grocery store, or blanket) worth about 10 US dollars was provided to the parents after each data collection session.

A. Fingerprint Readers

Two different fingerprint readers, a commercial 500 ppi fingerprint reader (Digital Persona U.are.U 4500 HD [20]) and a custom 1,270 ppi fingerprint reader designed by NEC [3],

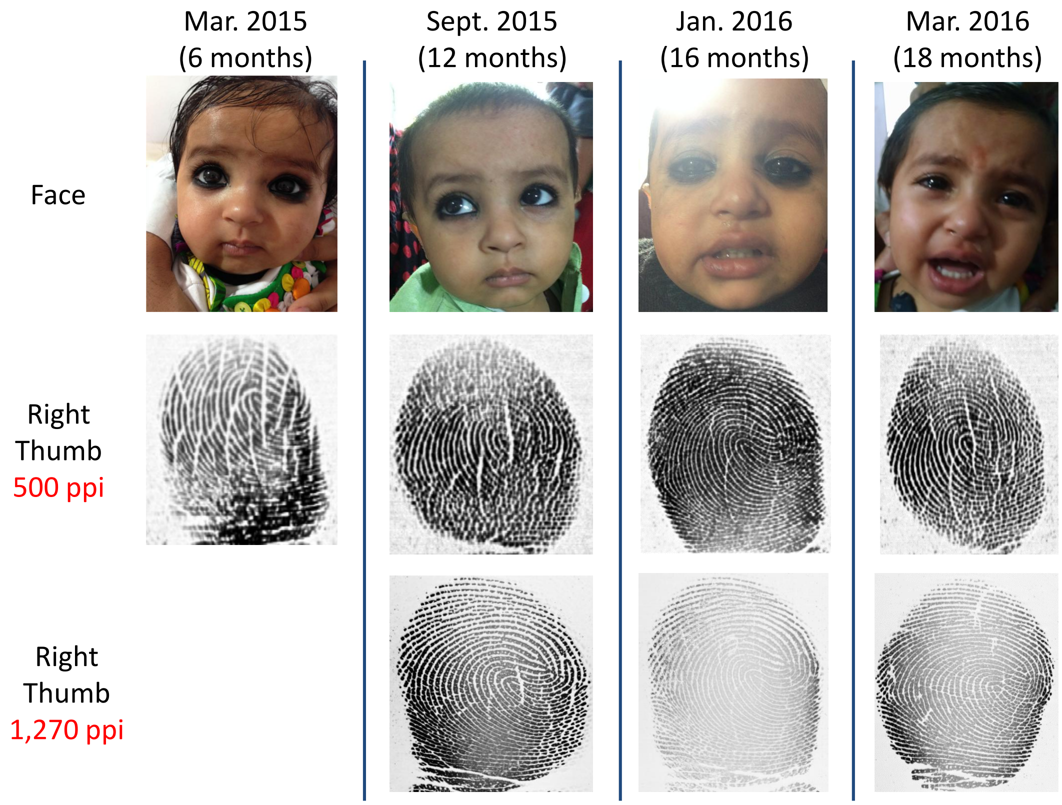


Fig. 5. Face and fingerprint images of a subject acquired during the four data collection sessions. Age of the subject at the time of each acquisition is shown in parenthesis. Right thumb print images captured using the 500 ppi Digital Persona U.are.U 4500 HD fingerprint reader and the custom 1,270 ppi NEC fingerprint reader are shown in the second and third rows, respectively. The NEC reader was not available during the first session.

were used for collecting child fingerprints. Whereas the 500 ppi reader was used in all four sessions, the 1,270 ppi reader became available starting session 2 (September 2015). Table I summarizes the technical specifications of the two readers. Compared to the 500 ppi reader, the 1,270 ppi reader is able to better capture the minute details (e.g. ridge endings and bifurcations) present on a child's finger (see Fig. 3). In contrast to the traditional Frustrated Total Internal Reflection (FTIR) based method used by the 500 ppi reader, the 1,270 ppi reader uses the Scattered Light Direct Reading (SLDR) method for fingerprint sensing that purportedly provides fingerprint images with high fidelity [3]. Another key characteristic of the 1,270 ppi reader is the placement of a manual capture button at the bottom of the reader. This allows the operator to capture fingerprint images based on realtime visual feedback.

TABLE I
TECHNICAL SPECIFICATIONS OF THE TWO FINGERPRINT READERS USED FOR CAPTURING CHILD FINGERPRINTS.

Reader	U.are.U 4500 HD	Custom NEC reader
Technology	Optical FTIR	CMOS + SLDR
Capture Area (L×W mm^2)	14.6×18.1	35.4×21.8
Max. Resolution (ppi)	512	1270
Dimensions (L×W×H mm^3)	65×36×15.6	72×35×7.5
Capture Mode	Automatic	Manual

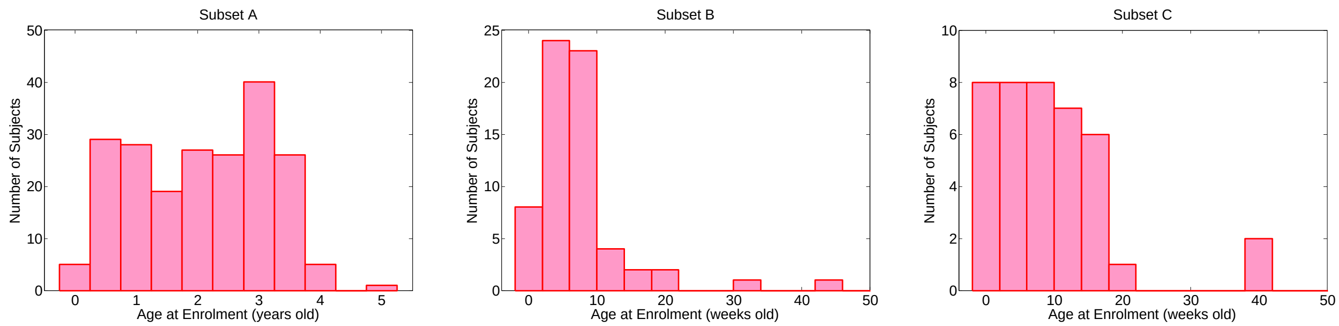
B. Data Collection Protocol

During each data collection session, three images each of the left and right thumb prints of all subjects were captured using the two fingerprint readers[7], and three face images were clicked in succession using the iPhone 5/5s rear camera. Fig. 5 shows a face image and a right thumb print image of a subject captured during each of the four data collection sessions. Due to the huge interest in our data collection, primarily because of the incentive we were providing, it was essential to maintain a high throughput. So, we could only spend about 3-5 minutes, on average, collecting face and fingerprint images of each subject. This requirement of high throughput is similar to the operational scenarios we are targeting (e.g. vaccination tracking in health camps).

C. Fingerprint Database

The child fingerprint database contains a total of 309 subjects (age range: 0-5 years) whose fingerprints were collected in four sessions. 204 subjects participated in the first data collection session in March 2015. Of these 204 subjects, 167, 180 and 178 subjects returned to provide their data in session 2 (September 2015), session 3 (January 2016) and session 4 (March 2016), respectively. Overall, 161 of the 204 subjects

[7] We only captured 500 ppi images during the first data collection session in March 2015 because the 1,270 ppi reader designed by NEC became available starting second data collection session (September 2015).



(a) (b) (c)

Fig. 6. Distribution of age at the time of enrolment of the subjects in the child fingerprint database. Subset A contains 204 subjects in the 0-5 year old age group. Subsets B and C contain 65 and 40 subjects, respectively, primarily in the 0-6 months old age group.

TABLE II

SUMMARY OF THE CHILD FINGERPRINT DATABASE COLLECTED IN THIS STUDY. COLUMNS 5, 6 AND 7 INDICATE THE NUMBER OF SUBJECTS THAT RETURNED FOR PROVIDING DATA IN SESSIONS 2, 3 AND 4, RESPECTIVELY. THE TIME LAPSE BETWEEN FIRST AND LAST DATA COLLECTION SESSION FOR EACH SUBSET IS SHOWN IN THE LAST COLUMN. THE 4TH DATA COLLECTION SESSION TOOK PLACE IN MARCH, 2016.

Subset	**First Session**	**# Subjects (males)**	**Age Range (median age)**	**# Ret. Sess. 2**	**# Ret. Sess. 3**	**# Ret. Sess. 4**	**Time Lapse ($\triangle T$)**
Subset A	1 (Mar. 2015)	204 (95)	0-5 (2.0) yrs	167	180	178	12 mos
Subset B	2 (Sep. 2015)	65 (33)	0-42 (6.1) weeks	*n.a.*	52	50	6 mos
Subset C	3 (Jan. 2016)	40 (18)	0-42 (7.6) weeks	*n.a.*	*n.a.*	30	2 mos

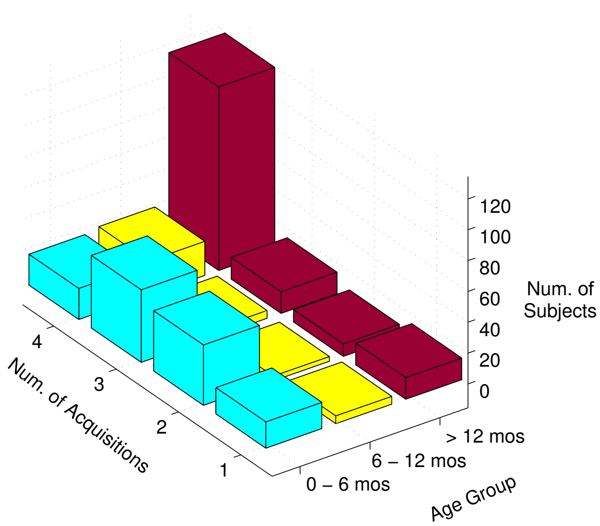


Fig. 7. 3D histogram showing the aggregate number of times fingerprints were collected from subjects in different age groups.

attended all four sessions. We refer to this subset of 204 subjects as *subset A*. Fig. 6 (a) shows the age distribution of the subjects in subset A. Because the initial set of 204 subjects did not have adequate representation from the 0-6 month old age group, we recruited an additional 105 subjects mostly in the 0-6 month old age group in sessions 2 and 3; there were 65 and 40 new subjects in sessions 2 and 3, respectively. We refer to these sets of 65 and 40 subjects as *subset B* and *subset C*, respectively. For the subjects in subsets B and C, only 1,270 ppi fingerprint images were captured because of their very young age. Figs. 6 (b) and (c) show the age distribution of the subjects in subsets B and C.

Table II summarizes the collected child fingerprint database. Fig. 7 shows a 3D histogram indicating the number of times fingerprints were acquired from subjects in different age groups. Most subjects older than 12 months provided their fingerprints in all four data collection sessions. On the other hand, majority of subjects younger than 6 months of age were recruited after the first data collection session and their fingerprints were subsequently acquired in the following data collection sessions.

IV. CHILD FINGERPRINT RECOGNITION

In principal, there are two major covariates that impact child fingerprint recognition accuracy: (i) the age of the child at the time of enrolment, and (ii) the time lapse between enrolment and query fingerprint images. To analyze the effect of these covariates on child fingerprint recognition accuracy, we conduct both verification (1:1 comparison) and search (1:N comparison) experiments using a state-of-the-art AFIS.

A. Evaluation Metrics

Two different evaluation metrics are computed for the verification scenario, (i) *true accepts* which is the number of subjects that can be correctly verified to have been previously enrolled, and (ii) *false accepts* which is the number of subjects that are incorrectly verified as previously enrolled. True accept rate (TAR) and false accept rate (FAR) are then computed to measure how frequently true accepts and false

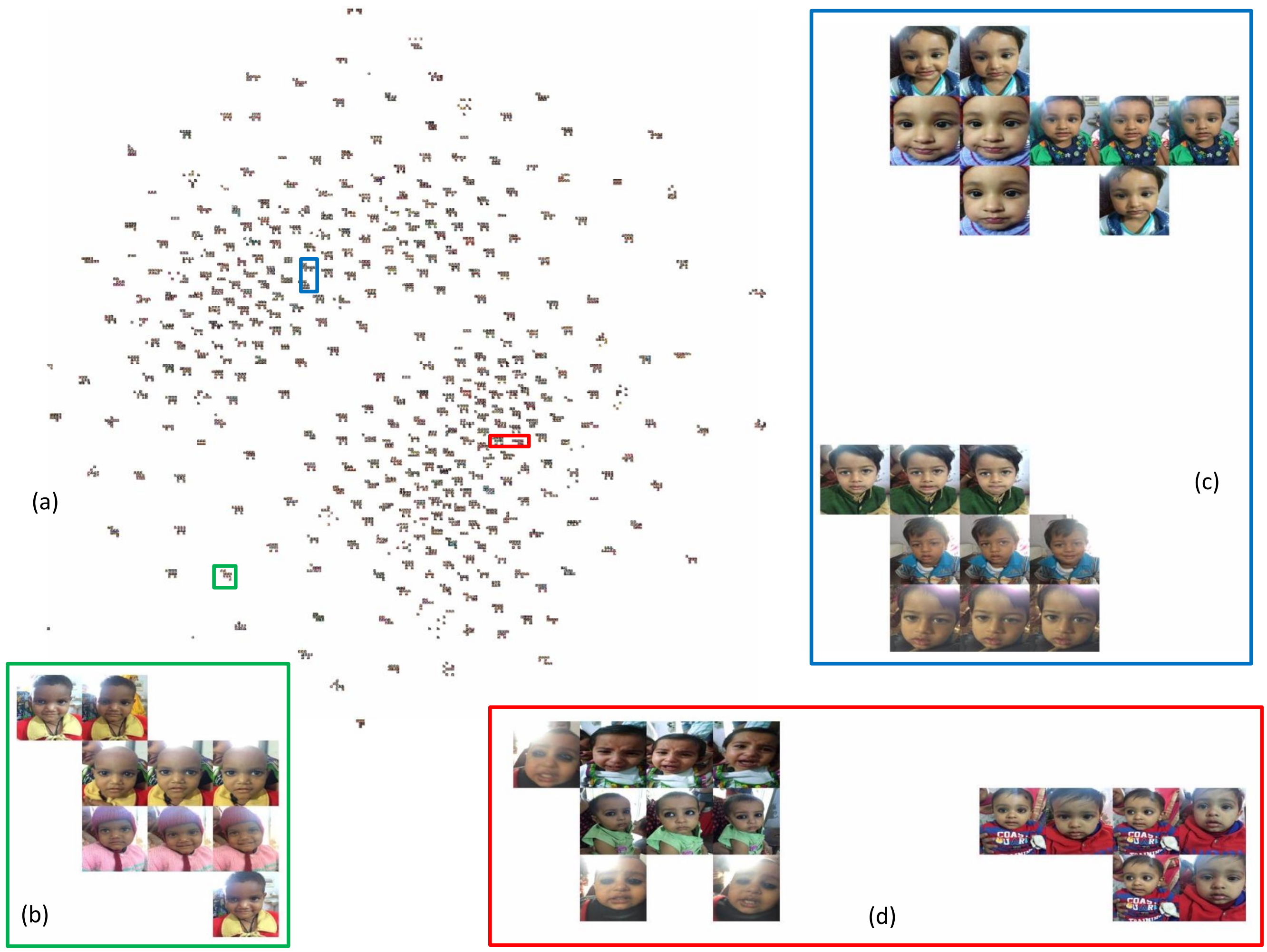


Fig. 8. A 2D t-SNE embedding [26] of child face images computed using the similarity score matrix generated by the AFIS for 1,270 ppi fingerprint images in subset A. The entire 2D embedding with 204 subjects is shown in (a). Images in (b), (c) and (d) show the close up of the rectangular regions marked in green, blue and red, respectively, on the 2D embedding in (a). Child face images are clustered by identity using fingerprint similarity. This indicates that fingerprint is a reliable identifier for child recognition.

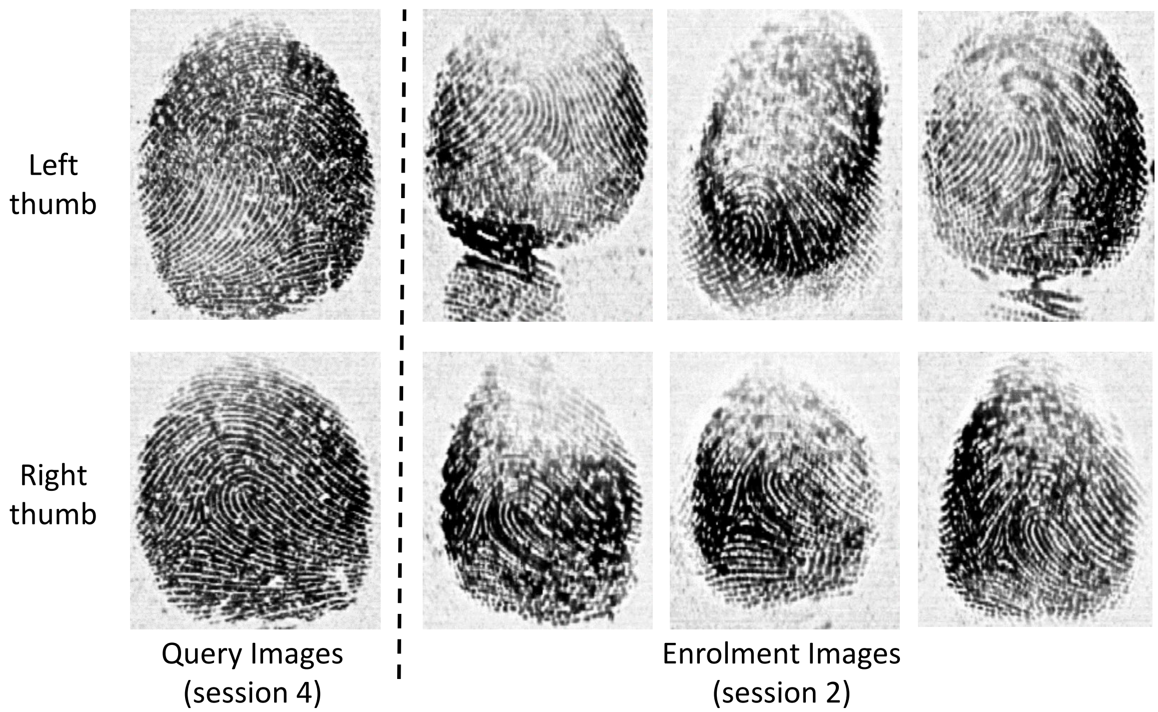
accepts are observed, respectively. In the search mode, the captured fingerprint is compared against an enrolment database containing fingerprints of known subjects, and a candidate list of the top-K matches is retrieved from the database. The rank-1 hit rate, i.e. the proportion of search queries for which the corresponding mated fingerprint is retrieved as the top candidate in the list, is used as the performance evaluation criteria. Open set search is planned for subsequent studies.

B. Experimental Protocol

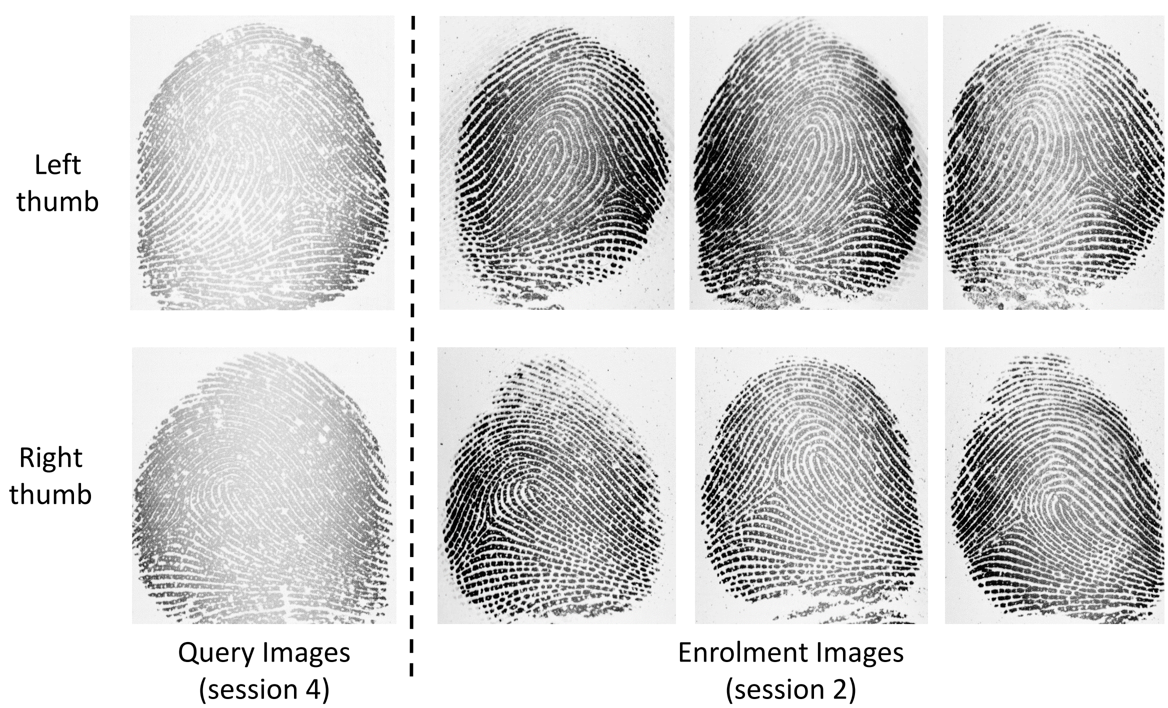
Before conducting the comparison experiments, the 500 ppi fingerprint images in subset A are upsampled by a factor of 1.8 whereas the 1,270 ppi images are downsampled by a factor of 0.71. The upsampling/downsampling of images is necessary to ensure that the ridge spacing in child fingerprint images (4-5 pixels) approximates the ridge spacing in adult fingerprint images (8-9 pixels) because the AFIS used to conduct the experiments is designed for adult fingerprint images. For subsets B and C that contain fingerprints of subjects primarily in the 0-6 months old age group, this upsampling/downsampling is not required because the ridge spacing in 1,270 ppi images is appropriate for the AFIS. Further, in case of search experiments, an additional 32,768 fingerprint images of 16,384 children (one image each of the left and right thumb) provided by VaxTrac[8] are included in the enrolment database (gallery). These images were captured by health care workers using different 500 ppi readers at multiple vaccination camps in Benin, Africa, are of varying quality but similar in characteristics to the 500 ppi fingerprint images captured in this study. Because these images were captured using 500 ppi readers, they are also upsampled by a factor of 1.8.

For comparison experiments, the three images each of the left and right thumb prints acquired when a subject first provides data are assumed to be enrolled. These images are referred to as *enrolment* images. Each of the three images of the two thumb prints of the subject acquired in subse-

[8]http://vaxtrac.com/



(a) 500 ppi fingerprint images



(b) 1,270 ppi fingerprint images

Fig. 9. Sample enrolment and query fingerprint images of left and right thumbs of a child captured in sessions 2 and 4 (time lapse = 6 months), respectively: (a) 500 ppi, and (b) 1,270 ppi fingerprint images. Age of the subject at the time of enrolment was 8 months. The identity of the subject could not be successfully verified using 500 ppi query images due to poor quality; however, successful verification was achieved using 1,270 ppi images.

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

Fig. 10. Left thumb print images (500 ppi) of a child captured at four different ages: (a) 3 months, (b) 9 months, (c) 13 months, and (d) 15 months. One can observe visually that better quality fingerprint images are acquired as the child ages.

TABLE III
VERIFICATION PERFORMANCE (TAR%@FAR=0.1%) ON 500 PPI AND 1,270 PPI CHILD FINGERPRINTS IMAGES OF 162 SUBJECTS FROM SUBSET A. SESSION 2 IS THE ENROLMENT SESSION AND SESSION 4 IS THE VERIFICATION SESSION (TIME LAPSE = 6 MONTHS).

Age at enrolment (# subjects)	**500 ppi**	**1,270 ppi**
6-12 months (20)	95%	98.9%
12-60 months (142)	99.5%	100%

quent data collection sessions are assumed to be separate verification/search queries. These images are referred to as *query* images. The similarity scores of a query with the three enrolment images are combined using sum fusion. Further, the similarity scores of a pair of left and right thumb print queries are fused together using sum fusion in order to improve the verification/search performance.

C. Fingerprint as a Child Identifier

Fig. 8 shows a 2D t-SNE embedding [26] of child face images based on the similarity matrix generated using the AFIS scores for the 1,270 ppi fingerprints in subset A. One can visually observe that face images are clustered by identity using fingerprint similarity scores. This indicates that fingerprint is a reliable identifier for distinguishing children based on their identity.

D. Performance Comparison: 500 ppi v. 1,270 ppi fingerprints

The objective of this experiment is to perform comparative analysis of the recognition performance obtained using 500 ppi and 1,270 ppi fingerprint images. For a fair comparison, verification experiments are conducted on fingerprints of 162 subjects from subset A that were captured during both session 2 in September 2015 and session 4 in March 2016 (time lapse = 6 months) using the two fingerprint readers. The images acquired in session 2 are, therefore, the enrolment images and those acquired in session 4 are the query images.

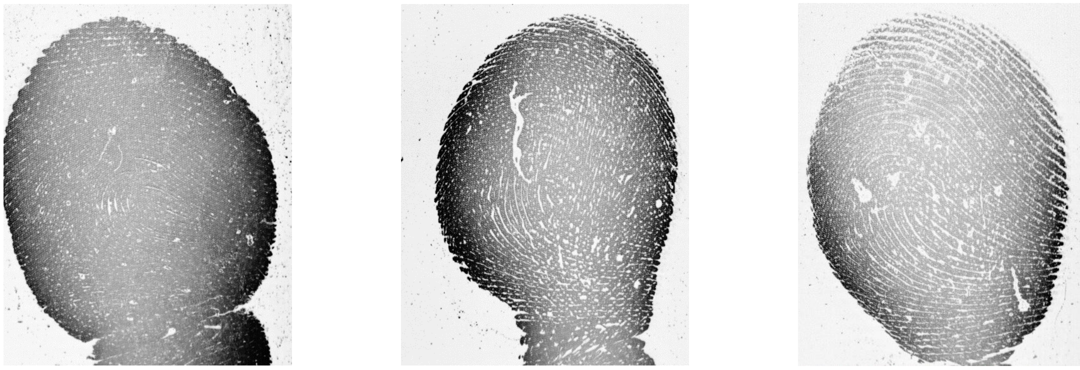
Table III shows the verification performance of the AFIS for different age groups. For subjects that were older than 12 months at the time of enrolment, verification performance using 1,270 ppi fingerprints (100% TAR at 0.1% FAR) is only marginally better compared to 500 ppi fingerprints (99.5% TAR at 0.1% FAR). However, for subjects between 6-12 months of age at the time of enrolment, 1,270 ppi fingerprints provide higher verification performance (98.9% TAR at 0.1% FAR) than 500 ppi fingerprints (95% TAR at 0.1% FAR). Fig. 9 shows sample 500 ppi and 1,270 ppi enrolment and query fingerprint images of a subject captured in sessions 2 and 4, respectively. The age of the subject at the time of enrolment was 8 months. For this subject, the quality of 500 ppi query fingerprints was inadequate and caused verification failure. However, the quality of 1,270 ppi fingerprints was found to

TABLE IV
VERIFICATION PERFORMANCE (TAR%@FAR=0.1%) ON 500 PPI AND 1,270 PPI FINGERPRINT IMAGES OF THE 204 SUBJECTS IN SUBSET A. SESSIONS 1 AND 2 ARE, RESPECTIVELY, THE ENROLMENT SESSIONS FOR 500 PPI AND 1,270 PPI IMAGES. PERFORMANCE IS REPORTED FOR DIFFERENT TIME LAPSE BETWEEN ENROLMENT AND QUERY IMAGES.

	Age at enrolment (# subjects)	**Time lapse (months)**			
		4	6	10	12
500 ppi	0-6 months (21)	n.a.	66.7%	77.3%	71.1%
	6-12 months (30)	n.a.	92.8%	96.2%	94.9%
	12-60 months (153)	n.a.	100%	100%	100%
1,270 ppi	6-12 months (23)	100%	98.9%	n.a.	n.a.
	12-60 months (145)	100%	100%	n.a.	n.a.

TABLE V
SEARCH PERFORMANCE (RANK-1 HIT RATE %) ON 500 PPI AND 1,270 PPI FINGERPRINT IMAGES OF THE 204 SUBJECTS (AGE RANGE: 0-5 YEARS) IN SUBSET A. SESSIONS 1 AND 2 ARE, RESPECTIVELY, THE ENROLMENT SESSIONS FOR 500 PPI AND 1,270 PPI IMAGES. ADDITIONAL 32,768 FINGERPRINT IMAGES ARE INCLUDED IN THE ENROLMENT DATABASE. PERFORMANCE IS REPORTED FOR DIFFERENT TIME LAPSE BETWEEN ENROLMENT AND QUERY IMAGES.

	Age at enrolment (# subjects)	**Time lapse (months)**			
		4	6	10	12
500 ppi	0-6 months (21)	n.a.	66.7%	77.3%	72.8%
	6-12 months (30)	n.a.	99.0%	96.2%	95.8%
	12-60 months (153)	n.a.	100%	100%	100%
1,270 ppi	6-12 months (23)	100%	99.4%	n.a.	n.a.
	12-60 months (145)	100%	100%	n.a.	n.a.



(a) (b) (c)

Fig. 11. Right thumb print images (1,270 ppi) of a child captured at three different ages: (a) 1 day, (b) 4 months, and (c) 6 months. The quality of the captured images is inadequate for reliable recognition.

be adequate for successful verification.

Note that the minimum age of a subject in subset A at the time of session 2 is 6 months. Hence, verification performance of subjects in the 0-6 month age group is not reported in Table III. The results for the 0-6 month old age group are reported in the following experiments.

E. Performance Evaluation: Subset A (0-5 years old)

Analogous to the earlier experiment, the first session during which fingerprints of a subject are captured is the enrolment session, and subsequent sessions when his fingerprints are acquired are verification/search sessions. Therefore, for the 500 ppi U.are.U 4500 reader, session 1 is the enrolment session and sessions 2, 3 and 4 are the verification/search sessions. On the other hand, for the 1,270 ppi NEC reader, session 2 is the enrolment session and sessions 3 and 4 are the verification/search sessions.

Table IV reports the verification performance of the AFIS on 500 ppi and 1,270 ppi child fingerprint images, respectively, for different time lapse between enrolment and verification queries. In line with our earlier experimental results, 1,270 ppi fingerprints provide higher verification performance compared to 500 ppi fingerprints. Contrary to expectations, the verification performance for both 500 and 1,270 ppi images, particularly for subjects that are in the 0-6 months age group, improves with elapsed time between enrolment and query images. While this may sound counter-intuitive, the primary reason for this performance improvement is the quality of the query fingerprint for the same enrolment image. As a child becomes older, better quality query fingerprints are acquired and consequently, the similarity between the query and enrolment prints increases (see e.g. Fig. 10).

Table V presents the results of the search experiments conducted using the AFIS on 500 ppi and 1,270 ppi child fingerprint images, respectively, for different time lapse between enrolment and search queries. Akin to the verification scenario, search performance is better using 1,270 ppi images compared to 500 ppi images, and higher search performance is obtained with elapsed time between enrolment and query images.

TABLE VI
VERIFICATION PERFORMANCE (TAR%@FAR=0.1%) ON 1,270 PPI FINGERPRINT IMAGES OF THE 105 SUBJECTS (AGE RANGE: 0-6 MONTHS) IN SUBSETS B AND C. SESSIONS 2 AND 3 ARE, RESPECTIVELY, THE ENROLMENT SESSIONS FOR SUBSETS B AND C. PERFORMANCE IS REPORTED FOR DIFFERENT TIME LAPSE BETWEEN ENROLMENT AND QUERY IMAGES.

Subset (# subjects)	**Time lapse (months)**		
	2	4	6
Subset B (65)	n.a.[9]	18.0%	9.8%
Subset C (40)	31.9%	n.a.[9]	n.a.[9]

TABLE VII
SEARCH PERFORMANCE (RANK-1 HIT RATE %) ON 1,270 PPI FINGERPRINT IMAGES OF THE 105 SUBJECTS (AGE RANGE: 0-6 MONTHS) IN SUBSETS B AND C. SESSIONS 2 AND 3 ARE, RESPECTIVELY, THE ENROLMENT SESSIONS FOR SUBSETS B AND C. ADDITIONAL 32,768 FINGERPRINT IMAGES ARE INCLUDED IN THE ENROLMENT DATABASE. PERFORMANCE IS REPORTED FOR DIFFERENT TIME LAPSE BETWEEN ENROLMENT AND QUERY IMAGES.

Subset (# subjects)	**Time lapse (months)**		
	2	4	6
Subset B (65)	n.a.[9].	33.6%	31.1%
Subset C (40)	42.2%	n.a.[9]	n.a.[9]

F. Performance Evaluation: Subsets B and C (0-6 months old)

Most subjects in subsets B and C are in the 0-6 month old age group. To analyze the recognition performance for the 1,270 ppi fingerprint images acquired from these subjects, we follow the same experimental protocol as the previous two experiments. For subjects in subset B, session 2 is assumed to be the enrolment session and sessions 3 and 4 are the verification/search sessions. On the other hand, for subjects in subset C, session 3 is the enrolment session and session 4 is the verification/search session.

Tables VI and VII report the verification and search performance, respectively, for this experiment. Verification accuracy

[9]Performance not available because the indicated time lapse between enrolment and query images is not present in the given subset.

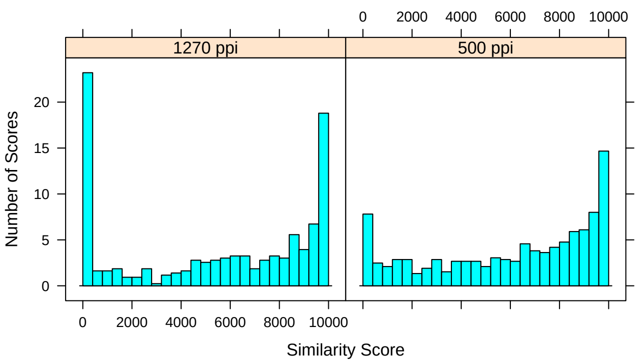


Fig. 12. Distributions of AFIS genuine scores obtained from comparisons of 500 ppi and 1,270 ppi fingerprint images of 186 and 223 subjects, respectively. The genuine scores here are comparisons of the enrolment session to all subsequent verification/search sessions, where Session 1 and Session 2 are the enrolment sessions for the 500 ppi and 1,270 ppi readers, respectively. The high frequencies for the minimum (0) and maximum (9999) scores are due to the AFIS censoring scores below or above these values. Frequency of 0 scores is higher for 1,270 ppi images compared to 500 ppi images because most 1,270 images were acquired from 0-6 months old subjects and are of poor quality.

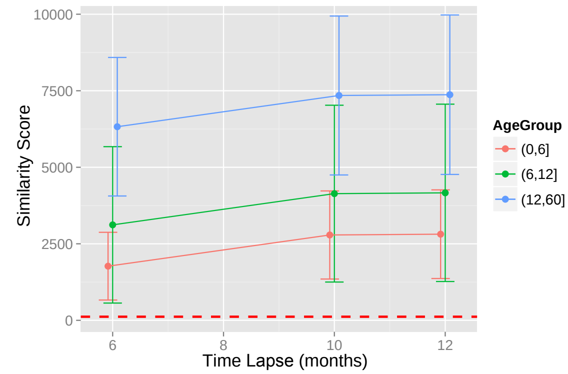
is only 9.8% at 0.1% FAR and rank-1 hit rate is mere 31.1% for subjects in subset B (time lapse = 6 months) despite using high-resolution 1,270 ppi images. The primary reason for the significant drop in performance is the poor quality of enrolment prints captured from subjects in this age group (see, e.g., Fig. 11). Capturing good quality fingerprints of 0-6 months old children sufficient for the purpose of recognition, therefore, remains an impending challenge.

V. Persistence of Child Fingerprint Recognition Accuracy

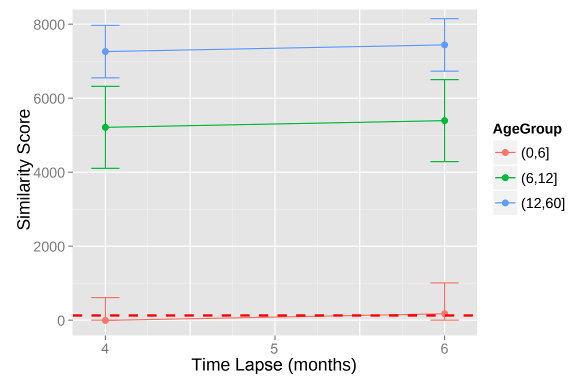
To study the persistence of child fingerprint recognition accuracy, the *genuine* similarity scores are modelled using mixed-effects regression models [27] [28]. Regression modelling aims to address the following questions:

- What is the trend in genuine similarity scores as a child ages (i.e. increasing time lapse between enrolment and query fingerprints)?
- Are there significant differences between the trends of different age groups ($(0, 6]$, $(6, 12]$, and $(12, 60]$ months old)?

For this analysis, similar to [29], we assume that the first acquisition is the enrolment session (Session 1 for the 500 ppi reader and Session 2 for 1,270 ppi reader), and fingerprints from all subsequent sessions are verification/search attempts. We then apply sum fusion over the multiple images per thumb, as well as the left and right thumbs, to obtain one score per verification/search session. Separate regression models are fit to the genuine similarity scores obtained from the 500 ppi and 1,270 ppi readers. Fig. 12 shows that the score distributions (for both readers) appear to be left and right *censored*. The true values of the scores below (above) the minimum (maximum) values are unknown because the AFIS sets them to the minimum/maximum values. The mixed-effects models used in this analysis assume that the scores are the true values.



(a)



(b)

Fig. 13. Estimated mean trends (with 95% confidence intervals) of genuine similarity scores obtained from mixed-effects regression models. Trends are shown for subject age groups $(0, 6]$, $(6, 12]$, and $(12, 60]$ months old for both the 500 ppi and 1,270 ppi readers in (a) and (b), respectively.

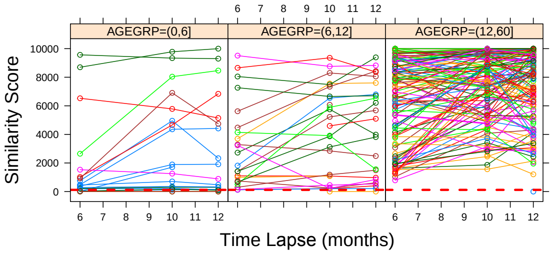
A. 500 ppi Reader: 12 months time lapse

For the 500 ppi reader, a total of 186 subjects first came in Session 1 (Mar. 2015) and then returned for at least one other data collection session. Each subject has one to three genuine scores corresponding to time gaps of 6, 10, and 12 months since enrolment. A piecewise linear model is used to analyze the scores at these three time points:

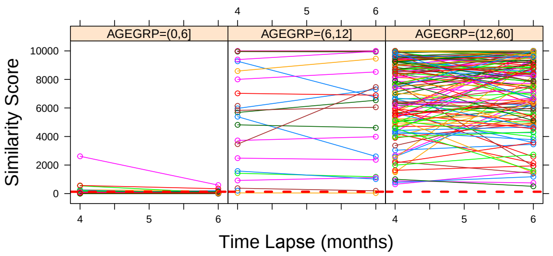
$$y_{ij} = \beta_0 + \beta_1 \triangle T_{ij} + \beta_2 \triangle T^*_{ij} + \beta_3 AGE_i \\ + b_{0i} + b_{1i} + b_{2i} + \varepsilon_{ij}, \tag{1}$$

where y_{ij} is the genuine score of subject i from the jth verification session, $\triangle T_{ij}$ is the time lapse between the enrolment and jth sessions ($j \in \{2, 3, 4\}$), $\triangle T^*_{ij} = max(0, \triangle T_{ij} - 10)$ is a function of the time lapse that allows for a piecewise linear trend with "knot" at 10 months, AGE_i is the age group of subject i ($(0, 6]$, $(6, 12]$, or $(12, 60]$ months old), b_{0i}, b_{1i}, and b_{2i} are *random-effect* terms [27], [28] that allow each subject to have his/her own intercept and slopes for the two segments of the trend, and ε_{ij} is the residual error.

Fig. 13 (a) shows the resulting marginal mean trends for each age group from the mixed-effects model in (1). Interestingly, mean genuine similarity scores actually *increase* from 6 to 10 months time lapse. This is because the quality of the fingerprints acquired improves as the subject ages (see, e.g., Fig. 10). We also observe that the additional 2 months time



(a)



(b)

Fig. 14. Raw longitudinal profiles of genuine similarity scores generated by the AFIS on (a) 500 ppi fingerprint images of 186 subjects, and (b) 1,270 ppi fingerprint images of 223 subjects. The thresholds at 0.1% FAR are shown as red dashed lines. Age group range is indicated in months.

between sessions 3 and 4 (Jan. and Mar. 2016) has no effect (the scores stay constant).

As for age group differences, trend for $(12, 60]$ months old group is significantly different from $(0, 6]$ months old group due to overall higher similarity scores. The *rates* at which the scores change were *not* significantly different between the age groups. This is demonstrated by the parallel lines in Fig. 13. Note that the threshold at 0.1% FAR is well below the mean trends for all age groups in Fig. 13 (a); hence, errors are due to only a few subjects with poor quality images, almost all of whom are younger than 12 months old (see Fig. 14 (a)).

B. 1,270 ppi Reader: 6 months time lapse

For the 1,270 ppi reader, a total of 223 subjects[10] attended Session 2 (Sep. 2015) and then returned for at least one other data collection session. Here, each subject has one or two genuine scores corresponding to time gaps of 4 or 6 months since enrolment. The model used for genuine scores from the 1,270 ppi fingerprints is similar to the model in (1):

$$y_{ij} = \beta_0 + \beta_1 \triangle T_{ij} + \beta_2 AGE_i + b_{0i} + b_{1i} + \varepsilon_{ij}. \quad (2)$$

However, note that this is a straight line (not piecewise) since there are only two genuine scores and two time points for the 1,270 ppi reader.

Fig. 13 (b) shows the resulting marginal mean trends for each age group from the mixed-effects model in (2). We observe that mean genuine similarity scores remain constant from 4 to 6 months time lapse, and all age groups are significantly different from one another. In this case, however, the mean trend for the $(0, 6]$ months old age group falls along the threshold at 0.1% FAR, indicating much poorer accuracy for the youngest subjects. This could be due to the larger sample size for this age group, as we recruited additional very young subjects for enrolment with the 1,270 ppi reader in Session 2 (Subset B in Fig. 6). Fig. 14 (b) shows that the genuine scores for subjects $(0, 6]$ months old in Session 2 are much lower than the other age groups.

[10]For this analysis, we use *all* subjects with 1,270 ppi fingerprint images from Session 2 and at least one other subsequent session. These 223 subjects are from Subset A and Subset B in Fig. 6.

VI. Conclusions and Future Work

We have addressed the following two fundamental questions: (i) do fingerprints of children possess the salient features necessary to uniquely recognize each child?, and if so, (ii) at what age is it possible to capture a child's fingerprints with sufficient fidelity for recognition? For this purpose, we initiated a data collection effort at the Saran Ashram hospital, Dayalbagh, India, and fingerprinted 309 children (age range: 0-5 years) in four different sessions over a one year period. For the first time ever, we demonstrate the successful capture of fingerprints of a child as young as 6 hours old using a custom 1,270 ppi fingerprint reader. Empirical evaluation conducted on the captured fingerprint data using a state-of-the-art AFIS shows that 500 ppi fingerprints suffice for recognizing children at least 12 months of age (TAR = 99.5% at FAR = 0.1%), while 1,270 ppi fingerprints are required to recognize children that are 6 months or older (TAR = 98.9% at FAR = 0.1%). Statistical analysis with mixed-effects models shows that (i) the age at enrolment has a larger effect on genuine scores generated by the AFIS than the time lapse between enrolment and query images, and (ii) the genuine similarity scores do not significantly decrease due to the 6-12 months time lapse. These results demonstrate the potential of fingerprint recognition as a feasible solution for child identification in applications such as vaccination tracking, improving child nutrition, national identification programs, and the emerging interest in identity for lifetime.

Given these encouraging results, we plan to continue our data collection effort by capturing fingerprints of the same subjects annually for four more years. This will enable us to further extend our longitudinal study and to better evaluate the use of fingerprints for providing lifelong identity.

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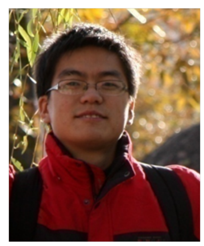

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