Open access • Proceedings Article • DOI:10.1109/BTAS.2014.6996252

Recognizing infants and toddlers using fingerprints: Increasing the vaccination coverage — Source link

Anil K. Jain, Kai Cao, Sunpreet S. Arora

Institutions: Michigan State University

Published on: 29 Dec 2014 - International Journal of Central Banking (IEEE)

Topics: Fingerprint (computing) and Fingerprint recognition

Recognizing Infants and Toddlers Using Fingerprints: Increasing the Vaccination Coverage

Anil K. Jain, Kai Cao and Sunpreet S. Arora
Department of Computer Science and Engineering
Michigan State University
East Lansing, Michigan 48824
Email: {jain, kaicao, arorasun}@cse.msu.edu

Abstract

One of the major goals of most national, international and non-governmental health organizations is to eradicate the occurrence of vaccine-preventable childhood diseases (e.g., polio). Without a high vaccination coverage in a country or a geographical region, these deadly diseases take a heavy toll on children. Therefore, it is important for an effective immunization program to keep track of children who have been immunized and those who have received the required booster shots during the first 4 years of life to improve the vaccination coverage. Given that children, as well as the adults, in low income countries typically do not have any form of identification documents which can be used for this purpose, we address the following question: can fingerprints be effectively used to recognize children from birth to 4 years? We have collected 1,600 fingerprint images (500 ppi) of 20 infants and toddlers captured over a 30-day period in East Lansing, Michigan and 420 fingerprints of 70 infants and toddlers at two different health clinics in Benin, West Africa. We devised the following strategies to improve the fingerprint recognition accuracy when comparing the acquired fingerprints against an extended gallery database of 32,768 infant fingerprints collected by VaxTrac in Benin: (i) upsample the acquired fingerprint image to facilitate minutiae extraction, (ii) match the query print against templates created from each enrollment impression and fuse the match scores, (iii) fuse the match scores of the thumb and index finger, and (iv) update the gallery with fingerprints acquired over multiple sessions. A rank-1 (rank-10) identification accuracy of 83.8% (89.6%) on the East Lansing data, and 40.00% (48.57%) on the Benin data is obtained after incorporating these strategies when matching infant and toddler fingerprints using a commercial fingerprint SDK. This is an improvement of about 38% and 20%, respectively, on the two datasets without using the proposed strategies. A state-of-the-art latent fingerprint SDK achieves an even higher rank-1 (rank-10) identification accuracy of 98.97% (99.39%) and 67.14% (71.43%) on the two datasets, respectively, using these strategies; an improvement of about 23% and 24%, respectively, on the two datasets without using the proposed strategies.

1. Introduction

The United Nations Children's Fund (UNICEF)'s "2013 Progress Report on Committing to Child Survival: A Promise Renewed" [2] mentions that while more children now survive beyond their fifth birthday than ever before, the poorest nations still lose a large number of children to vaccine-preventable diseases. The 2011 Grand Challenges in Global Health Explorations Round 7 issued by the Bill and Melinda Gates Foundation [4] states that "each year approximately 25 million infants do not receive the necessary immunizations[1], and at least 2.4 million children die from vaccine-preventable diseases."

With the aim of eradicating vaccine-preventable diseases, routine and mandatory vaccination programs are a norm in high income countries. For instance, according to the Centers for Disease Control and Prevention (CDC), "in the United States, vaccination programs have eliminated or significantly reduced many vaccine-preventable diseases" [3]. Consequently, the child mortality rates have reduced considerably in high income countries. On the other hand, routine immunization programs have not been as effective in reducing the occurrence of vaccine-preventable diseases in low-income countries. VaxTrac[2], a non-governmental organization working in West-African countries, states that the "vaccine wastage rates are higher than 50% in some of the most challenging geographies", and "for every $100 in new vaccines purchased, $50 will never go into the arm of a child in need"[3]. As a result, the child mortality rates continue to be high in the low-income and developing countries.

An effective immunization program needs to keep track of which infants and toddlers have been immunized and how often they have received the required booster shots from birth to 4 years of age (Fig. 1 shows the UNICEF

[1] Vaccination and immunization are being used interchangeably here.
[2] http://vaxtrac.com
[3] http://vaxtrac.com/mission/challenge

Fig. 1: Universally recommended immunization schedule for infants by UNICEF [2].

(a) (b)

Fig. 2: Use of fingerprints for tracking the vaccination schedule of infants and toddlers in Benin, Africa. (a) Mothers waiting in a health clinic to get their children vaccinated, and (b) a healthcare worker fingerprinting a child before administering vaccination. These images were captured by the authors during their visit to the vaccination centers in and around Cotonou, Benin in June 2014.

recommended immunization schedule for infants; for CDC recommended schedule for children upto 6 years see [1]). In developing countries, typically, there are no national identification programs which can be used to identify children throughout the immunization schedule[4]. This raises the following question: can fingerprints, or, for that matter any other biometric modality, be used to identify children from birth to 4 years of age?

Some efforts have been made to investigate the viability of using different biometric traits for identifying infants and toddlers. In 1899, Sir Francis Galton [11] first studied the variations encountered in the inked fingerprint impressions of an infant captured over time (from about 9 days to 4.5 years of age). He concluded that it was not feasible to identify infants in the age range of 0-2.5 years using inked fingerprint impressions. More recently, the Joint Research Center of the European Commission published a technical report [5] devoted to the question of whether or not automated fingerprint recognition for children is feasible. The study concluded that (i) children can be identified using fingerprints when the time difference between the two captured impressions is less than 4.5 years, and (ii) image quality is a decisive factor in fingerprint recognition. Gottschlich *et al*. [12] studied the effect of adolescent growth on the accuracy of fingerprint matching systems, and showed that (i) fingerprint growth can be modelled using an isotropic growth model, and (ii) matching accuracy of fingerprint systems can be improved by upscaling the fingerprint images using this model when matching fingerprint images of adolescents collected over time.

Corby *et al*. [7] studied the viability of using commercial sensors to capture iris images of 1.5-8 year old children. They reported a high failure to enroll (FTE) rate of approximately 57%, although the recognition accuracy for the enrolled subjects was very high (about 99%). Tiwari *et al*. [20] and Bharadwaj *et al*. [6] captured face images of newborns (0-3 days old) and concluded that it was difficult to capture good quality face images due to (i) gross head reflexes, and (ii) pose and expression variations. Weingaertner *et al*. [21] investigated the use of palmprints and footprints for identifying newborns (0-2 days old). Manual matching accuracy was reported to be approximately 83% and approximately 67% for palmprints and footprints of newborns, respectively. Lemes *et al*. [15] used a 1000 ppi commercial sensor to capture palmprint images of 20 newborns (0-2 days old). They reported palmprint recognition accuracy of approximately 95%. Pela *et al*. [17] and Thompson *et al*. [19] investigated the use of footprints acquired using traditional ink on paper methods for identification of newborns (0-2 days old) and concluded that footprints cannot be captured reliably. Kotzerke *et al*. [13] proposed to use the creases on footprint for manual identification of infants, where the footprint images were obtained by ink and paper acquisition. Two researchers with considerable experience in ridge-based biometrics correctly classified 19 of the 20 pairs.

Although a number of different biometric modalities for identifying children have been explored, there is no clear consensus on (i) whether it is feasible to recognize infants and toddlers using biometrics, and (ii) if biometric recognition is indeed feasible, which modality is best suited for this task. Based on a number of considerations such as ease of capture (palmprints are difficult to capture because newborns and infants keep their fists closed), parental concerns (e.g., infrared illumination for iris capture), persistence of biometric trait (facial characteristics change over time), in our opinion, fingerprints appear to be the most viable biometric for infant and toddler recognition (see Tab. 1). Indeed, VaxTrac has developed a mobile vaccine registry system which uses fingerprints to identify children in Benin[1] (Fig. 2(b)). In the VaxTrac system, the left and right thumb prints of both the child and his mother are collected. If the child's fingerprints cannot be matched successfully, mother's fingerprints are used for establishing/verifying the child's identity. While VaxTrac does not report the matching accuracy of children's fingerprints, they mention that they almost invariably end up using the mother's fingerprints for this purpose because matching children's fingerprints fails quite often [5]. Continued efforts are, therefore, needed to advance the fingerprint technology, both sensing technology as well as matching algorithm behind the mobile vaccine registry system. In this paper, we present the initial results of our ongoing study on using fingerprints to recognize infants and toddlers.

[4]http://vaxtrac.com/mission/solution

[5]Based on our personal communication with VaxTrac

Biometric Trait	Ease of Capture	Persistence	Parental Concerns
Face	Moderate	Low (facial aging)	Minor
Fingerprint	Difficult	High	Moderate
Iris	Difficult	High	Major (infrared illumination, obtrusive capture process)
Footprint	Difficult	Not known	Minor (routinely used in U.S. hospitals)
Palmprint	Difficult	High	Moderate

Tab. 1: Comparison of the feasibility of using different biometric modalities for infant and toddler recognition. The subjective entries in this table are solely based on the opinion of the authors.

2. Capturing Fingerprint Images of Children

For the aforementioned application involving identification of infants and toddlers using their fingerprints, the first major challenge is to capture good quality fingerprint images. This is primarily because of the following reasons:

- *Semi to non-cooperative subjects*: Most infants and toddlers do not place their fingers on the fingerprint sensor on their own. It is difficult to force them to place their fingers properly on the sensor for more than a few seconds. As a result, often there is insufficient time for the fingerprint sensors to capture good quality images. Typically, one has to hold the child's fingerprint on the sensor and apply some pressure.
- *Oily/wet finger skin*: The finger skin of newborns usually has a waxy coating on it reportedly due to a higher percentage of sterol esters to prevent excessive wetting of finger skin [14]. Besides, infants and toddlers typically have the habit of sucking their fingers, which affects their finger skin texture. The texture of oily/wet finger skin directly manifests itself in the captured fingerprint impression, thereby affecting the fingerprint image quality.
- *Small sized fingers:* Most fingerprint sensors are designed to sense adult fingers. When presented with smaller sized infant and toddler fingers, the finger detection module built into the sensors sometimes fails to detect the presence of the finger to trigger the fingerprint capture process.

2.1. Initial Efforts

As a first step, we explored the use of two state-of-the-art smartphone cameras (iPhone 5S and Samsung Galaxy S4 Zoom) for capturing fingerprint images of children. Despite the use of the built-in flash, special light fixture, and an image magnifier, the acquired fingerprint images were not of sufficient quality for feature extraction and matching. Next, we experimented with using several handheld 500 and 1000 ppi optical fingerprint sensors. Based on our experience, desirable characteristics of a fingerprint sensor for capturing fingerprints of infants and toddlers are (i) *portability* because the sensor has to be brought close to the child's finger for capturing fingerprints, (ii) *compact and comfortable sensor platen* to be able to place the child's finger properly on the sensor platen to initiate the fingerprint capture process, and (iii) *fast capture speed* because it is difficult to hold the child's finger steady on the sensor platen for more than a few seconds in most cases.

(a) (b)

Fig. 3: Fingerprint acquisition using the Digital Persona U.are.U 4500 optical fingerprint reader of (a) a five months old infant in East Lansing, United States, and (b) of a two month old infant in Benin, West Africa.

Based on the results of our initial experiments, U.are.U 4500, a 500 ppi optical fingerprint reader from Digital Persona [16] provides the best quality fingerprint images of infants and toddlers. Therefore, we use this optical reader for the remainder of our data collection (see Fig. 3). Further, in order to obtain high quality images, we (i) clean the sensor platen periodically to prevent residue buildup from previous fingerprint captures which appears as background noise in the image, (ii) clean the child's finger before placing it on sensor platen, and (iii) apply external pressure to the child's finger to increase the contact area between the finger and the sensor.

2.2. Data Collection

Fingerprint images of 90 infants and toddlers were captured using the Digital Person U.are.U 4500 optical fingerprint reader at two different locations, East Lansing, Michigan in the United States and Cotonou, Benin in West Africa. We refer to this database as the Michigan State University Infant and Toddler Fingerprint (MSU-ITF) database.

2.2.1 East Lansing data

Initial data collection was done in East Lansing, Michigan. A total of 1,600 fingerprint impressions (two index fingers and two thumbs) from 20 subjects in the age range [0-4] years were captured. Data was collected over five sessions, about 1 week apart, and four fingerprint impressions per finger were collected in each session. Face images were also collected in each session but they were not used for matching. Instead, they were used for displaying the retrieved subjects from the database so that the health care worker can visually confirm the child's identity. Fig. 4 shows the face image and fingerprint images of one of the subjects collected in East Lansing.

2.2.2 Benin data

We also travelled to Benin to collect operational data from two different health clinics. The first was a rural health clinic where fingerprint images of 20 subjects were captured in an open air shelter in sunlight. The second was an urban clinic, where fingerprints of 50 subjects were obtained.

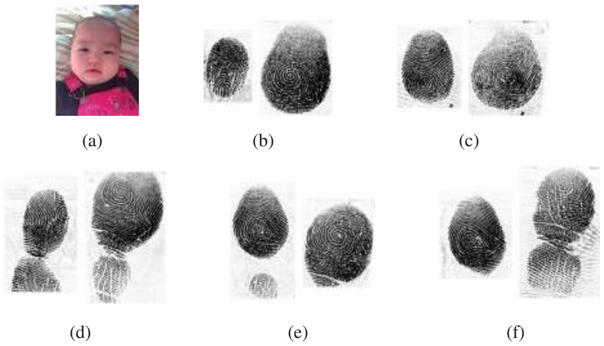


Fig. 4: Fingerprint images (left thumb and left index finger) and face image of a four month old subject in the MSU-ITF database captured in East Lansing. (a) Face image; (b)-(f) fingerprint images of the left thumb and left index finger at the 1st, 2nd, 3rd, 4th and 5th acquisition sessions; each session is separated from the preceding session by approximately 1 week. Fingerprint images shown here have been manually cropped for better illustration.

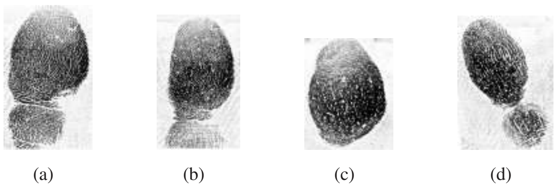


Fig. 5: Fingerprint images (left thumb and left index finger) of (a) and (b) a four month old subject, and (c) and (d) a five month old subject in the MSU-ITF database captured in Benin. Fingerprint images shown here have been manually cropped for better illustration.

This data was captured in a closed room with fixed lighting. Note that data was captured in a single session on two different days in the two clinics. Three impressions each of the left index and left thumb fingers were captured resulting in a total of 120 fingerprint impressions of 20 subjects being captured in the rural clinic and 300 fingerprint impressions of 50 subjects captured in the urban clinic. Fig. 5 shows the fingerprint images of two of the subjects captured in Benin.

3. Matching Fingerprint Images of Children

Once usable fingerprint impressions are acquired, the next task is to automatically match the captured impressions with high accuracy. Automatic matching of the captured fingerprints is a challenging problem because of the following reasons:

1. *Poor image quality*: Despite cleaning the child's finger before capturing the fingerprint image, some oil/water is at times retained in the finger skin leading to the capture of poor quality fingerprint impressions. See Fig. 6(a).
2. *Non-linear distortion and partial impressions*: Children usually have more resilient and elastic skin which leads to large non-linear distortion in the captured impressions. Additionally, due to small finger size, the overlap between two impressions of the same finger is typically small. See Fig. 6(b).
3. *Difficulty in feature extraction*: The average inter-ridge spacing in the MSU-ITF database is 4.9 pixels which is about half of the 8.4 pixels of inter-ridge spacing in FVC2002 DB1 [9]. Due to this, a commercial fingerprint SDK fails to extract several genuine minutiae from the child's fingerprint image even though the image appears to have clear ridge structure. See Fig. 6(c).
4. *Variations in finger skin condition*: Fig. 6(d) shows two different impressions of the same finger of the same subject. Although these impressions were collected just one week apart, their image quality is quite different.

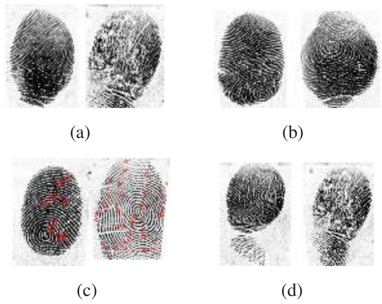


Fig. 6: Challenges in matching fingerprint images of infants and toddlers. (a) Oily/waxy finger skin resulting in poor quality impressions, (b) large non-linear distortion and small overlapping region between two impressions of the same finger, (c) difficulty in feature extraction from the fingerprint images of a five months old child (left) compared to that of an adult (right) using a commercial fingerprint SDK, (d) difference in quality due to variations in finger skin condition in the two impressions of the same finger taken one week apart.

3.1. Matching Strategies

To handle the aforementioned challenges, we devised the following matching strategies to be used in conjunction with a commercial fingerprint SDK and a state-of-the-art latent SDK[6]

1. *Upsample the acquired image*: Fingerprint SDKs expect ridge-spacing values of about 9 pixels (a typical value for adult fingerprints). Given that the inter-ridge spacing for infants and toddlers is about 4.9 pixels, upsample the images to increase the average ridge spacing before submitting it to the SDK.
2. *Fuse match scores of multiple enrolled templates*: Enroll multiple templates of each finger in the gallery. Compare each query image against all the templates of the finger and fuse the obtained match scores.
3. *Fuse match scores of two fingers*: Fuse match scores obtained from matching two fingers of each subject to boost the matching performance.
4. *Update gallery over time*: Instead of simply using the templates from the initial enrollment session, include templates from all previous sessions in the gallery.

[6] We experimented with the latent SDK because several challenges in automatically matching latent fingerprints are similar to those encountered in matching infant and toddler fingerprints.

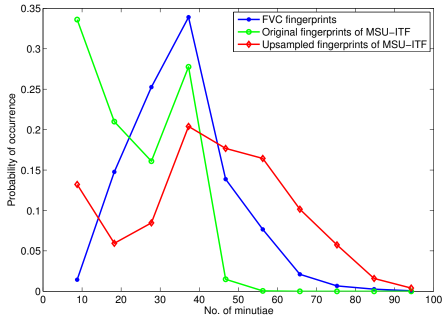


Fig. 7: Distribution of no. of minutiae in fingerprint images in FVC2000, FVC2002 and FVC2004 (blue), original images in MSU-ITF database (green) and upsampled images (scale value = 1.8) in the MSU-ITF database (red).

	Scale parameter					
	1.0	1.2	1.4	1.6	1.8	2.0
TAR	23.51%	40.55%	53.41%	59.45%	62.25%	60.82%

Tab. 2: TAR (%) @ FAR=0.1% for different scale parameters using the commercial fingerprint SDK on the East Lansing data.

3.2. Matching Experiments

Matching experiments are conducted using (i) a commercial fingerprint SDK and (ii) a state-of-the-art latent fingerprint SDK for both the verification and identification scenarios.

3.2.1 Determining the upsampling factor

Bilinear interpolation (MATLAB function: imresize) is used for upsampling the images. Tab. 2 compares the True Accept Rate (TAR) at a fixed False Accept Rate (FAR) of 0.1% for different scale values using the commercial fingerprint SDK on the East Lansing data. Note the increase in TAR from 23.51% to 62.25% as the scale value is increased from 1.0 to 1.8. Based on this observation, 1.8 is selected as the value for upsampling the fingerprint images. In terms of image size, a 392×357 fingerprint image is upsampled to 706×643.

Fig. 7 compares the distributions of the number of minutiae in the original and upsampled fingerprints in the MSU-ITF database (with scale value 1.8) and 9,600 fingerprints from FVC2000 [8], FVC2002 [9] and FVC2004 [10]. Note that after upsampling, the distribution of the number of minutiae in the MSU-ITF database comes close to that in the FVC databases.

The average NFIQ value[7] [18] for the upsampled fingerprints in the MSU-ITF database is 1.9 compared with 3.0 in the FVC databases. The standard variation of NFIQ values for the upsampled fingerprints in the MSU-ITF database and FVC databases is 0.9 and 1.4, respectively. Even though NFIQ values indicate that children's fingerprints are of good quality, visually their quality is not good. This discrepancy could be because NFIQ has not been designed for children fingerprints [5].

[7]NFIQ value ranges from 1 to 5, with 1 indicating the highest quality and 5 indicating the lowest quality fingerprint.

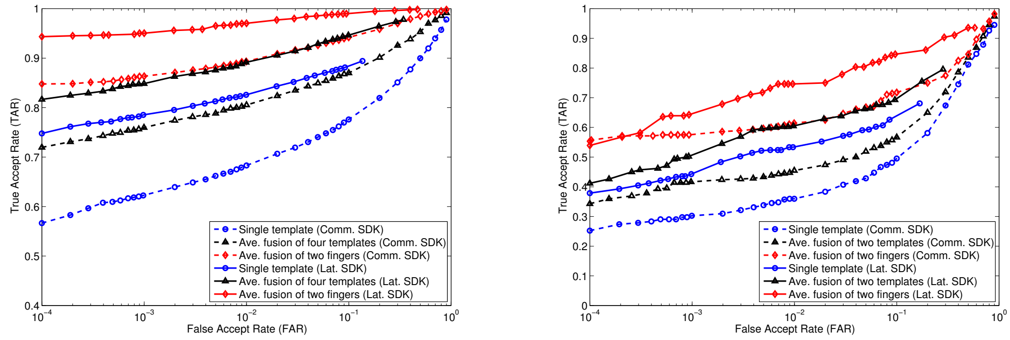
3.2.2 Fingerprint verification

Verification is the most commonly encountered scenario in field operations. When a child who has previously been immunized needs to be administered subsequent vaccinations, the health worker enters basic information into the system such as the ID of the child. He then collects the child's fingerprints to verify his identity before administering the vaccine. In our experiments, the verification protocol followed is analogous to that used in FVC.

1. *Matching against each enrolled template*: Matching a query to each individual enrolled template in the gallery from the East Lansing data results in a TAR of 62.25% and 78.52% at a FAR of 0.1% using the commercial fingerprint SDK and the latent fingerprint SDK, respectively. On the Benin data at the same FAR of 0.1%, a TAR of 30.24% is obtained using the commercial fingerprint SDK whereas using the latent SDK results in a TAR of 44.29%.
2. *Fusion of match scores from multiple enrolled templates*: To see the effect of the number of templates on the verification performance of the two SDKs, TAR is computed assuming there are two or four enrolled templates in the gallery. Average fusion scheme is found to give the best results. At a FAR of 0.1%, the TAR after fusion improves from 62.25% to 71.01% and from 78.52% to 82.52% for the commercial fingerprint SDK and the latent fingerprint SDK, respectively, when using two templates during the verification from the East Lansing data. When all four enrolled templates are used, the verification performance improves to 75.97% and 84.84% for the two matchers on this data. On the other hand, for the data collected in Benin, match score fusion of two templates improves the TAR at a FAR of 0.1% from 30.24% to 41.67% for the commercial fingerprint SDK. For the latent SDK, this scheme improves the TAR from 44.29% to 50.24%.
3. *Fusion of match scores from two fingers*: The best accuracy (average of different combinations of two fingers) was again obtained using average match score fusion. Using a combination of two fingers improves the TAR (at a FAR=0.1%) to 86.34% and 95.04% for the commercial fingerprint SDK and the latent fingerprint SDK, respectively, on the East Lansing data. The same scheme improves the TAR to 57.50% and 64.27% for the two matchers, respectively, on the Benin data. As a comparison with adult fingerprint recognition accuracy, VaxTrac reports a TAR of 99.0% at 0.1% FAR or the same matching scenario[8].

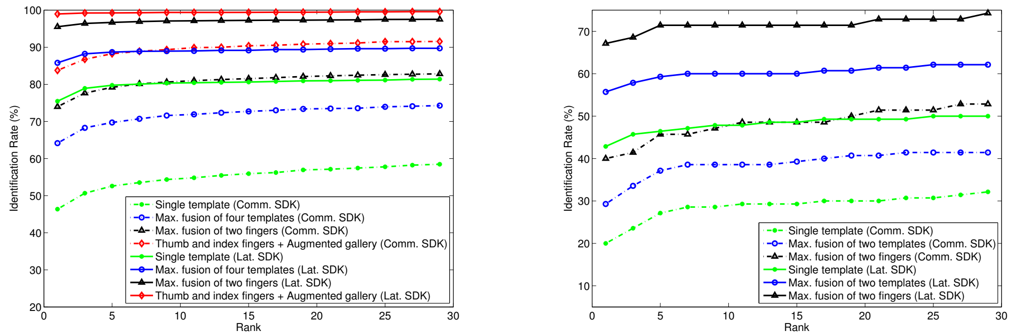
Fig. 8(a) and Fig. 8(b) show the Receiver Operating Characteristics (ROC) curves for East Lansing and Benin data, respectively, using different matching strategies in conjunction with the two SDKs. Note the improvement in TAR at different FAR thresholds.

[8]Based on our personal communication with VaxTrac.



(a) (b)

Fig. 8: Receiver Operating Characteristics (ROC) curves for average fusion of multiple templates and two fingers using the commercial fingerprint SDK (shown as dashed curves), and the latent fingerprint SDK (shown as solid curves) on (a) the East Lansing data, and (b) the Benin data in the MSU-ITF database.



(a) (b)

Fig. 9: Cumulative Match Characteristic (CMC) curves for average fusion of multiple templates, fusion of two fingers and use of extended gallery using the commercial fingerprint SDK (shown as dashed curves), and the latent fingerprint SDK (shown as solid curves) on (a) the East Lansing data, and (b) the Benin data in the MSU-ITF database.

3.2.3 Fingerprint identification

In field operations, identification mode of operation is meaningful when the child coming for immunization can not present any credentials. Further, identification mode will be needed for de-duplication of the fingerprint database. Experiments are conducted to investigate the performance of the proposed matching strategies on the identification accuracy. A total of 32,768 fingerprints of 16,384 subjects (two thumbs per subject and one impression per thumb), which were collected by VaxTrac, are used to enhance the gallery.

The baseline performance assumes that a single template of a single finger per subject is present in the gallery. Matching queries acquired in subsequent sessions to the first enrolled template directly yields a rank-1 identification accuracy of 46.38% and 75.46% using the commercial fingerprint SDK and the latent fingerprint SDK, respectively, on the East Lansing data. On the Benin data, rank-1 accuracies of 20% and 42.85% are obtained, respectively, using the two SDKs.

When multiple templates of a finger are enrolled, we match the query against all the enrolled templates. This is followed by fusing the match scores obtained from matching the probe against multiple templates using the max fusion strategy. For the East Lansing data, the rank-1 identification accuracy improves to 64.16% and 85.80%, respectively, for the two SDKs when using four templates. Using the two enrolled templates in the gallery improves the rank-1 identification accuracy to 29.29% and 55.71% for the commercial fingerprint SDK and the latent fingerprint SDK, respectively, on the Benin data.

A max fusion of the match scores obtained from matching two different fingers with multiple templates in the gallery further improves the identification accuracy. With two finger fusion strategy (average of different combinations of two fingers) in addition to multiple enrolled templates, the rank-1 identification rate improves to 73.98% for the commercial fingerprint SDK on the East Lansing data. For the latent fingerprint SDK, the rank-1 accuracy improves to 95.52% using the same strategy on this data. On the data collected in Benin, the commercial fingerprint SDK obtains a rank-1 identification rate of 40.00% whereas

	One finger (one template)	One finger (four templates)	Two fingers (four templates)	Thumb and index fingers (four templates) + updated gallery
Commercial fingerprint SDK	46.37 (54.53)	64.16 (71.78)	73.98 (80.79)	83.76 (89.58)
Latent fingerprint SDK	75.46 (80.42)	85.80 (88.95)	95.52 (97.11)	98.97 (99.39)

Tab. 3: Rank-1 (Rank-10) identification accuracies (%) for different scenarios using the two SDKs on the MSU-ITF database captured in East Lansing (total of 1600 fingerprints of 80 fingers of 20 subjects). The background database is enhanced using 32,768 infant fingerprints collected by VaxTrac in Benin.

	One finger (one template)	One finger (four templates)	Two fingers (four templates)
Commercial fingerprint SDK	20.00 (29.29)	29.29 (38.57)	40.00 (48.57)
Latent fingerprint SDK	42.86 (47.86)	55.72 (60.00)	67.14 (71.43)

Tab. 4: Rank-1 (Rank-10) identification accuracies (%) for different scenarios using the two SDKs on the MSU-ITF database captured in Benin (total of 420 fingerprints of 140 fingers of 70 subjects). The background database is enhanced using 32,768 infant fingerprints collected by VaxTrac in Benin.

the latent fingerprint SDK's rank-1 identification accuracy improves to 67.14% when fusing the match scores obtained from two fingers. Note that the fusion of thumb and the index finger showed the best performance improvement.

Updating the gallery by using templates from multiple sessions further improves the matching performance. The rank-1 identification accuracy improves from 73.98% to 83.77% for the commercial fingerprint SDK on the East Lansing data when using the updated gallery in conjunction with thumb and index finger fusion. The rank-1 accuracy of the latent fingerprint SDK improves from 95.52% to 98.97% using this strategy on the same data. Note that this scheme could not be evaluated on the Benin data because fingerprint images were acquired in a single session at the two health clinics.

Fig. 9(a) and Fig. 9(b) show the Cumulative Match Characteristics (CMC) curves for East Lansing and Benin data, respectively, using different matching strategies in conjunction with the two SDKs. Note the improvement in identification accuracies of the two SDKs. Tab. 3 and Tab. 4 summarize the identification accuracies for different scenarios on the two databases.

For the vaccination tracking application, we propose to use fingerprints to retrieve the top N subjects from the database and then display the face images of the retrieved candidates. This allows the health worker to verify the true mate of the query. This way, if we display the top-10 retrieved candidates (N =10), identification accuracy can potentially be improved to 99.39% and 71.43% (based on using the latent fingerprint SDK on the East Lansing and Benin data, respectively). Fig. 10 gives an example for $N = 9$, where the face image (denoted using a red boundary) is the true mate for the given fingerprint query.

There are two main reasons for the failure to retrieve the true mate at rank-N: (i) query impressions or templates are of very low quality (see Fig. 11 (a)); (ii) small overlap and large distortion between the query and the templates in the gallery (see Fig. 11 (b)). With augmented gallery, we are able to retrieve the true mate for the query in Fig. 11 (b), but the query in Fig. 11 (a) does not lead to successful mate.

Note that, in general, the identification accuracies obtained by the two fingerprint SDKs used in our experiments

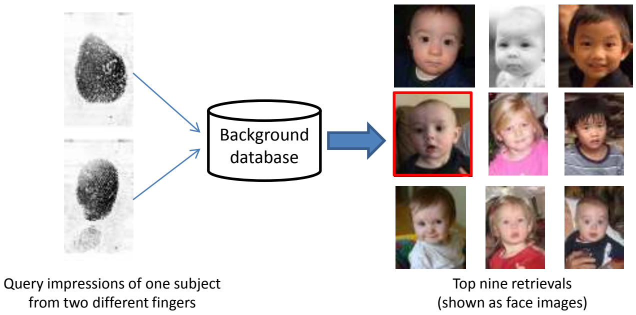


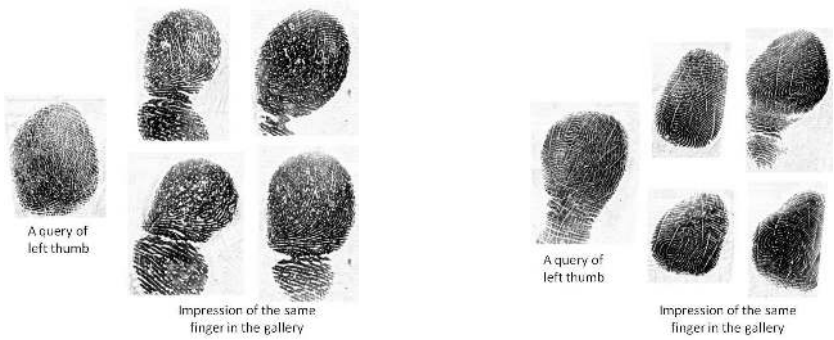
Fig. 10: Illustration of fingerprint based identification (left thumb and left index finger) where the face images of the top-9 retrieved subjects are shown; the face image with red boundary is the true mate.

are lower on the Benin data compared to the East Lansing data. In our opinion, this is because of the following reasons:

- *Acquisition environment*: High temperature and humidity in Benin result in non-ideal operating conditions for fingerprint sensors. On the other hand, East Lansing has comparatively lower temperature and is significantly less humid, As a result, the environment is more suited for fingerprint capture in East Lansing. Besides, the East Lansing data was captured in children's homes as opposed to health clinics in Benin.
- *Difference in age of subjects*: Most subjects in the East Lansing data are over 6 months old whereas in Benin, most subjects are younger than 6 months. Younger children typically have the habit of sucking their fingers affecting the finger skin texture and as a result, adversely affecting the fingerprint image quality.

4. Conclusions and Future Work

Vaccine-preventable diseases continue to take a heavy toll on children in geographical regions and countries without a high immunization coverage. For improving the immunization coverage, an effective immunization program needs to keep track of the vaccination schedule of children. In this paper, we have investigated the viability of using fingerprints for identifying toddlers and infants (age range of 0-4 years) for this application. A total of 1,600 fingerprint images of four fingers each from 20 subjects were collected over a period of 30 days in East Lansing, United States and 420 fingerprints of two fingers each from 70 subjects were collected in two different health clinics in Benin. The captured images of infants and toddlers were upsampled to facilitate reliable feature extraction using commercial SDKs. Fusion of multiple templates and multiple fingers are investigated as potential matching strategies, to improve the matching performance of a commercial fingerprint SDK and a state-of-the-art latent fingerprint SDK. Our experimental results show that fusing the matching results of the thumb and index fingers (using two/four templates per finger) when matching against an extended gallery of 32,768



(a) (b)

Fig. 11: Two unsuccessful identification examples from two different subjects. (a) The query and gallery impressions are all of low quality and (b) there is only a small overlap and large distortion between the query and impressions in the gallery.

infant fingerprints significantly improves the matching performance. Updating the gallery by including templates captured in all previous sessions further improves the rank-1 (rank-10) identification rate of a commercial fingerprint SDK to 83.8% (89.6%) and 40.00% (48.57%) for the East Lansing and Benin data, respectively. The rank-1 (rank-10) accuracy of state-of-the-art latent matcher improves to 98.97% (99.39%) and 67.14% (71.43%) using these strategies on the two datasets, respectively.

In future, we plan to explore alternative capture technologies for capturing fingerprints of infants and toddlers. We are also investigating ways to further improve the matching performance by (i) using an adaptive scale parameter depending on child's age because there is a large variation of fingerprint size in the age range of [0,4] and (ii) preprocessing the fingerprint images to enhance the ridge structure before submitting it to the fingerprint SDKs.

Acknowledgments

This research was facilitated by a grant from the Bill & Melinda Gates Foundation. We would like to thank Ken Werman and Tim Wood (Bill & Melinda Gates Foundation), Mark Thomas, Shawn Sarwar, Meredith Baker, Duncan Spencer, Fidele Marc and Thibaut (VaxTrac), and Kelly Climer (MSU) for their suggestions and support.

References

[1] 2014 recommended immunizations for children from birth through 6 years old. http://www.cdc.gov/vaccines/ parents/downloads/parent-ver-sch-0-6yrs.pdf.

[2] Committing to child survival: A promise renewed. http://www.unicef.org/lac/Committing_to_Child_Survival _APR_9_Sept_2013.pdf.

[3] Vaccines and immunizations. http://www.cdc.gov/vaccines /vac-gen/whatifstop.htm.

[4] Create low-cost cell phone-based solutions for improved uptake and coverage of childhood vaccinations, grand challenges explorations round 7. http://www. grand-challenges.org/MeasureHealthStatus/Topics/CellPhoneApps /Pages/Round7.aspx, 2011.

[5] Fingerprint recognition for children. Technical report, Institute for the Protection and Security of the Citizen, 2013. http://publications.jrc.ec.europa.eu/repository/bitstream/111 111111/29732/1/fingerprint

[6] S. Bharadwaj, H. Bhatt, R. Singh, M. Vatsa, and S. Singh. Face recognition for newborns: A preliminary study. In *4th IEEE BTAS*, pages 1–6, Sept 2010.

[7] P. M. Corby, T. Schleyer, H. Spallek, T. C. Hart, R. J. Weyant, A. L. Corby, and W. A. Bretz. Using biometrics for participant identification in a research study: a case report. *J. Am. Medical Informatics Assoc.*, 13(2):233–235, 2006.

[8] Fingerprint Verification Competition (FVC) 2000. http://bias.csr. unibo.it/fvc2000/.

[9] Fingerprint Verification Competition (FVC) 2002. http://bias.csr. unibo.it/fvc2002/.

[10] Fingerprint Verification Competition (FVC) 2004. http://bias.csr. unibo.it/fvc2004/.

[11] F. Galton. Finger prints of young children. *British Association for the Advancement of Science*, 1899.

[12] C. Gottschlich, T. Hotz, R. Lorenz, S. Bernhardt, M. Hantschel, and A. Munk. Modeling the growth of fingerprints improves matching for adolescents. *IEEE Transactions on Information Forensics and Security*, 6(3):1165–1169, Sept 2011.

[13] J. Kotzerke, S. Davis, K. Horadam, and J. McVernon. Newborn and infant footprint crease pattern extraction. In *20th IEEE ICIP*, pages 4181–4185, Sept 2013.

[14] H. C. Lee, R. Ramotowski, and R. Gaensslen. *Advances in Fingerprint Technology*. CRC press, 2010.

[15] R. D. P. Lemes, O. R. P. Bellon, L. Silva, and A. K. Jain. Biometric recognition of newborns: Identification using palmprints. In *the 1st IEEE IJCB*, pages 1–6, 2011.

[16] U.are.U 4500 Reader. http://www.digitalpersona.com/Finger print-Biometrics/Fingerprint-Readers/U-are-U-4500-Reader/, 2014.

[17] N. T. Pelagrave, M. V. Mamede, and M. S. Tavares. Critical analysis of plantar impressions of the newborn infant. *Rev Bras Enferm*, 29(4):100–5, 1976.

[18] E. Tabassi, C. Wilson, and C. Watson. Fingerprint image quality. *NISTIR 7151*, 2004.

[19] J. E. Thompson, D. A. Clark, B. Salisbury, and J. Cahill. Footprinting the newborn infant: not cost effective. *The Journal of Pediatrics*, 99(5):797–798, 1981.

[20] S. Tiwari, A. Singh, and S. K. Singh. Intelligent method for face recognition of infant. *International Journal of Computer Applications*, 52(4):36–50, 2012.

[21] D. Weingaertner, O. R. P. Bellon, L. Silva, and M. N. Cat. Newborn's biometric identification: Can it be done? In *VISAPP (1)*, pages 200–205, 2008.