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Biometric Recognition of Infants using Fingerprint, Iris and Ear Biometrics

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ABSTRACT Biometric recognition is often used for adults for a variety of purposes where an individual's identity must be ascertained. However, the biometric recognition of children is an unsolved challenge. Solving this challenge could protect children from identity theft and identity fraud, help in reuniting lost children with their parents, improve border control systems in combatting child trafficking, and assist in electronic record-keeping systems. In order to begin the development of biometric recognition systems for children, researchers collected fingerprint, iris, and outer ear shape biometric information from infants. Each modality provides different challenges. Where possible, the performance of existing hardware and software that was developed for adults was assessed with infants. Where necessary, novel hardware or software was developed. For the ear modality, existing hardware and software which have previously been applied to adults were applied to children. For the iris modality, existing hardware was used to acquire the images, while adjustments to the existing preprocessing algorithms were applied to cater for the localisation and segmentation of infant irises. For the fingerprint modality, novel hardware and image processing software were developed to acquire fingerprints from infants, and convert the images into a format which is backward compatible with existing international standards for minutiae extraction and comparison. The advantages and disadvantages of using each of these modalities during the first year of life were compared, based on both qualitative assessments of usage, and quantitative assessments of performance. While there is no conclusively best modality, recommendations of usage for each modality were provided.

INDEX TERMS Authentication, Biometrics, Ear recognition, Fingerprint recognition, Identification of persons, Identification of infants, Identity management systems, Iris recognition

I. INTRODUCTION

Recognition of infants and minors precisely from birth is becoming ubiquitous. The choice of biometric modality to use for infants and minors has always been a bottleneck due to imaging devices and uncooperative nature of infants. To mitigate these challenges a research project has been started with the aim of developing a prototype biometric recognition system to acquire biometric data from young children, and determine or verify the identities of these children from birth until they apply for their identification documents (which can be done at the age of 16 years in South Africa). To assess the performance of the existing and newly developed biometric acquisition and recognition systems for children and achieve the aim of the project, it is required to acquire biometric data from children and successfully compare this biometric data.

The benefits of developing such a system are manifold. The output of this research is meant to address issues of identity theft and fraud against children, help combat child trafficking, assist with reuniting small children who are lost with their parents, and improve healthcare management systems for children [1]–[5]

The unique challenge that is posed is that existing technologies are not capable of acquiring biometric information from newborn infants and successfully matching it to the same individuals during growth and adulthood with accuracy and reliability, thus leaving children vulnerable to exploitation in various ways, such as identity theft and child trafficking. As a first step in solving this challenge, this paper addresses the acquisition of biometric information from children during the first year of life.

There has been some research into developing biometric recognition systems for children. However, there are still challenges to overcome in creating a complete biometric system for infants and minors.

A review of several modalities was performed before reaching the decision to focus on the fingerprint, iris, and outer ear shape. These modalities were chosen after an assessment based on seven criteria of the desirability of biometric characteristics, namely: universality, uniqueness, permanence, collectability, performance, acceptability, and resistance to circumvention [6]. The analysis is summarised in Figure 1 and discussed in detail below.

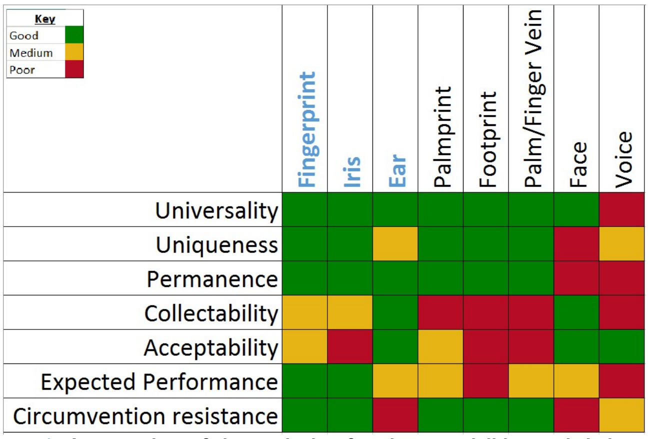

Figure 1: An overview of the analysis of various modalities and their suitability for use from birth to adulthood, based on several criteria.

Face [7]–[11] and speech [12], [13] biometrics may work for older children but are ineffective for newborn babies and toddlers. Footprint crease patterns [14]–[16] are promising for newborns but become less user-friendly as people become older and start wearing shoes. There are also concerns regarding the hygiene of feet which may come into contact with biometric sensors. These concerns also translate to research into using friction ridge patterns of the feet [17].

However, friction ridge patterns of the fingers (also called fingerprints) [1], [3], [18]–[21] and palms (palm prints) [17], [22] have shown more promise. The main challenge to acquiring fingerprints is that conventional fingerprint scanners do not acquire fingerprints at a sufficiently high resolution to resolve the fingerprints of newborn infants, and the contact nature of conventional scanners may, at times, be incompatible with the soft, malleable skin of infants. One approach has been to use higher resolution contact-based scanners to increase the accuracy of using a single fingerprint [1], [3], [18]–[21]. Another approach has been to collect fingerprints from all 10 fingers using a conventional scanner and fuse the scores for higher reliability [11]. While this latter approach has resulted in a high level of accuracy for toddlers aged 18 months and older, it may be difficult and time consuming to collect all 10 fingerprints from babies. Furthermore, the reliability as children grow bigger and the reliability of this method below the age of 18 months remains an open question. In this paper, we have proposed to use a novel fingerprint scanner which is a contactless device that uses a higher resolution than the previously cited works[1], [3], [11],[18]–[21].

While the friction ridge patterns on palms are conceptually similar to fingerprints and may be ergonomically easier to capture from infants, palms present other challenges. Due to the much larger area, hardware costs and data transfer requirements would increase if the full area of the palm is acquired. Alternatively, if a sub-region of the palm is acquired, consistency in repeatedly acquiring the same region may prove challenging.

Two other biometrics which have shown promise for young children are the outer ear shape [23], [24],[25] and the iris [11]. The advantage of the outer ear is that the collection of the biometric data is unobtrusive and hygienic since it is completely touchless. There is currently little research and commercial work done on ear recognition for children [26]. These includes work done by Tiwari et al. [23], [24], [27], [28] and Berra et al. [29] who attempted different recognition methods of newborns using ear images from hospitals. Kumar et al. [30] and Ntshangase et al. [31] evaluated the performance of recognition algorithms on ear recognition for children. There is still missing information in this field that needs to be addressed, such as the effect of growth on ear recognition, more details are presented in a paper by Ntshangase and Mathekga [26]. However, a larger dataset and longitudinal studies are required to obtain more reliable information about the permanence of the shape of the ear and the performance of ear recognition for children.

The iris is known to be effective for recognition from the age of 18 months and upwards. Daugman demonstrated in his pioneering iris recognition work that its recognition accuracy is seven times more than its major rival the fingerprint [32]–[36]. Even though Daugman reported high accuracy of the iris recognition system, no research was found where his works were extended to iris biometric recognition for infants and minors. The performance of iris image acquisition and recognition for children needs to be investigated. Preliminary findings of this research suggest that the variance in image quality between adult and infant iris images is minute [37].

In summary, in this paper, we report on the efforts towards developing and assessing three biometric recognition systems for infants using the fingerprint, iris, and outer ear shape biometric modalities. These systems have been developed independently, however, the long-term aim is to eventually fuse all three modalities in future work. This is done to improve the accuracy of each individual modality before they can be fused together.

The rest of the paper is structured in the following manner. Section II discusses related work. Section III describes the approach taken for each biometric modality. Section IV provided the experimental results and a discussion thereof, as well as a discussion on the lessons learned in this endeavor. Section V concludes the discourse and suggests avenues for future work.

II. RELATED WORK

The chosen biometric modalities were were the fingerprint, the outer ear shape and the iris pattern. The modalities were chosen after an assessment based on seven criteria of desirability of biometric characteristics, namely: universality, uniqueness, permanence, collectability, performance, acceptability, and resistance to circumvention [17]. In this section, for each of the three biometrics, we discuss their use for adults, literature research into applying them for children and what challenges remain to be solved for adoption of these technologies for the biometric recognition of children.

A. IRIS

Iris recognition has shown tremendous performance in adult candidates in various imaging conditions [32], [38]–[40]. As a caveat, these results require high levels of cooperation from the subjects, which makes it difficult for use on infants. However, with recent advances in imaging technologies [41]–[44] and iris recognition algorithms [45]–[53], researchers have now started to explore iris recognition for children.

In Jain et al. [54] various biometric modalities ranging from face, iris and fingerprint were exploited in order to identify, monitor and track children who are coming for vaccination. This was motivated by the fact that face biometric, iris biometric, and fingerprint biometric have been widely accepted with good recognition rates for adults but never tested on children. Basak et al., [11]] investigated various biometric modalities, and their results showed good performance for the iris and fingerprints as they performed much better than the face biometric. The main challenge with iris biometric for children is data acquisition since iris biometric is an active biometric. These same challenges were also observed by Basak et al. [11]. Nelufule et al. [37], have shown that the child irises are closely related to the adult irises in terms of quality assessment and usability as a biometric, provided that a clear image of the iris is obtained. Children at birth cannot corporate and need to be directed to look into the camera in order to capture an iris image. Therefore, in this work, we are exploring how existing software for adults perform on children.

B. EAR

According to literature reports, ear recognition for children was first introduced in 1960 by Fields et al. [55], who manually analysed ears of newborns on a database of 206 participants. After identifying the problem of incorrect identification of children, the authors investigated possible solutions to identify newborns using their ears. Fields et al. [55] concluded that visually ears can be used to distinguish amongst newborns.

In 2011, Tiwari et al. [23] investigated if automated ear recognition of newborns can be done. Their investigation was part of solving the problem of abduction, swapping and mix ups of infants while on hospital premises. Ear images were captured by first acquiring side face images. While this work is similar to the work presented by Fields et al. [55], the ear comparison methods are automated, although the ear region is manually segmented. The main contribution of this research was the preparation of a newborn ear database from 210 individuals. The authors had tested different ear matching algorithms and concluded that ears can be used as a biometric to identify newborns [23].

In 2012, Tiwari et al. [24] proposed an improvement of ear recognition for newborns by fusing ear features and soft biometrics. The considered soft-biometric data types are gender, blood group, height, and weight, which were used to enhance the accuracy for identification. The main contributions of their research are the design and implementation for the fusion of ear and soft biometric for recognition of 210 newborns, and the preparation of a combined ear images and soft-biometric database of newborns. The authors presented that the fusion of ear and soft-biometrics resulted in an improvement of approximately 5.59% over their previous identification system, which was based on ear recognition alone [24].

In 2013 Tiwari et al. [56] gathered a multimodal database of newborns for biometric recognition with soft biometrics [56]. The database includes physiological characteristics, namely face, ear and head print; and soft biometrics data, namely gender, height, weight and blood group of 280 newborns. The database contributes identity characteristics that may be useful for the authentication of newborns.

In 2014 Barra et al. [57] developed research on biometric authentication of newborn identities by means of ear patterns. The authors tested multiple ear matching algorithms to assess the accuracy of identification using ear recognition on a dataset of ear images of newborns. The authors concluded that ear images can be used to identify newborns [57].

In 2015, Tiwari et al. [27] proposed fully automated ear recognition for newborns. In addition to automatically locating, segmenting and cropping the ear region on the given ear image, Tiwari et al. [27] investigated a unique approach for the automatic recognition of newborns using 2D ear imaging. The authors presented that their investigation contributes a computationally effective solution to recognise newborns automatically. The proposed algorithm yields identification accuracy of 89.28% on a database of 210 subjects [27].

In 2015, Bargal et al. [58] developed a smartphone-based ear recognition application for managing medical records at on-site medical clinics in less developed countries where many individuals do not hold IDs. A pilot study was conducted on the developed application to test feasibility in naturalistic settings. However, it was not specified if the pilot study involved any data acquisition from children under the age of 18 years. Their future work includes performing a longitudinal study on infants under the age of three, whose ears will be developing over time. [58].

In 2016, Tiwari et al. [59] evaluated if several ear recognition algorithms that were developed for adult recognition can work on recognising newborns.

To the best of our knowledge, there has been no commercial automated system that performs ear recognition on children. However, an article released in October 2017 reported that the MATLAB Health Research Centre in Bangladesh and the Angkor Hospital for Children in

Cambodia, will partner to assess a range of biometric modalities such as fingerprints, irises, palm prints, ears and feet to determine which is most suitable for infants and young children [60].

FIGURE 2. Adult fingerprint acquired with conventional adult fingerprint scanner. The red block shows a region that is horizontally oriented, the green block shows a region that is vertically oriented, and the blue block shows a region that is diagonally oriented.

C. *FINGERPRINT*

1) DEVICE RESOLUTION

It is established that scanners designed for adults do not work for children, although the cut-off age is debated. The age below which adult scanners are ineffective for children is placed at 3 years according to Uhl and Wild [18], at 4 year according to a study by the Dutch government[19] and at 6 years according to the US National Institute of Justice [20].

Research on fingerprint acquisition from newborns has increased in recent years. A common measure of fingerprint acquisition devices is dots per inch (dpi), which is also referred to as pixels per inch (ppi). The international standard for adult fingerprint scanners requires 500dpi resolution [61] . This is insufficient to clearly resolve the fingerprint patterns on an infant's fingertip. This had led to research into higher resolution devices. Michigan State University (MSU) partnered with NEC to test a contact-based device with 1270dpi resolution [1][21][62]. Since then, MSU has developed a new contact-based device with 1900dpi resolution [63][64], while NEC has continued their research with trials in Kenya [65].

At birth, the distance between ridges on an infant's fingerprint is 100-150 microns [17]. For an adult, this is 450-500um. Since the ridge distance is up to 5 times smaller for infants compared to adults, we thus hypothesize that a resolution 5 times greater is needed to clearly resolve the ridges for all newborn infants, i.e. 2500dpi instead of 500dpi. It is hypothesized that the lower resolution in literature devices so far may explain the reduced accuracy for infants below 6 months. Thus, for the purposes of the study which is reported on in this paper, a device with a resolution of 2500dpi was developed.

Concurrent to the research which is reported in this paper, a device with a resolution of 3400dpi was developed by Saggese et al. [66], based on the reasoning that the valley width in relation to the entire ridge-valley distances is much smaller for infants than it is for adults. However, technical performance results of the increased resolution were not reported.

2) GROWTH MODELLING AND SCALING

Since children grow and do not remain at a constant size, this growth needs to be accounted for when comparing fingerprints from the same child, which were acquired at different ages. The size discrepancies must also be accounted for when children of different ages have their fingerprints captured using the same device.

A study by Gottslich et al. [3] which used longitudinal data of 48 juvenile individuals, aged 6 years and upwards, revealed two points which are relevant to this research. First, the growth of fingers was isotropic, i.e. the rate of growth in length and width was at a constant ratio. Second, there was a high correlation between growth of fingers and growth in height of the children. Gottslich et al. thus propose to use growth charts to model the growth of fingers.

Similarly, Jain et al. [67] assessed the size of fingerprints with participants between the ages of 6 months and 4 years. A range of scaling factors were tested until the best comparison scores could be achieved.

Alternately, in this work, instead of modelling the growth of the fingers, fingerprints can be scaled to a set size based on the ridge-valley distances, i.e. the distances between consecutive ridges in a fingerprint. For adult fingerprints acquired with a conventional 500dpi scanner, the number of pixels between two consecutive ridges is 9-10 pixels in regions where the pattern is vertically or horizontally oriented, and 6-7 pixels in regions where the pattern is diagonally oriented. These orientations are illustrated in Figure 2. This specification of pixels to represent a ridge and valley provides sufficient discretisation of the image data to clearly resolve boundaries between consecutive ridges. When fingerprints from unconstrained camera sources are resolved to the same pixel configurations, they are then of the correct "size", which is compatible with existing minutiae extraction and matching software. Similarly, scaling to a ridge-valley distance of 7 pixels was reported in Saggese et al. [66]

3) CONTACTLESS ACQUISITION

A challenge faced by contact-based acquisition, which was reported by Jain et al. [67], is that an infant's skin has a high elasticity and often suffers from folding and non-linear distortion. Further, it is expected that the epidermal layer is very thin for newborns, which may lead to complete loss of ridge-valley definition when contact is made with a scanner's platen. This would lead to smudging in many instances. To overcome this challenge, the scanner developed for this study was designed to be contactless, i.e. the area of the finger which was acquired for comparison was not in contact with any surface.

While contactless scanners for adults are in the experimental stage and slowly moving towards commercial use [68][69][70], the only other research on contactless acquisition for infants was the concurrent research by Saggese et al. [66], who also report that contactless acquisition performed better than contact-based acquisition for infants. However, no performance comparison results were reported between the two modes.

4) ILLUMINATION

Illumination also plays a role in the ability to capture clear fingerprints with contact-less devices. There have been some small preliminary studies into lighting. Wang et al. [71] recommend a blue polarized light at a 45 degree angle to the finger. They provide information on the construction of the light source and filters over the detector. However, their dataset is very small.

Labati et al. [72][73] used green light and blue illumination in ambient light conditions. They show success with a larger database. However, they also use a dual camera set up to construct 3D fingerprint data. Saggese et al. [66] report using polarized blue light as well.

III. PROPOSED APPROACH

Based on the assessment of related work, a different approach was chosen for each of the three modalities. The approaches are summarized in Table 1. Explanations for the chosen approaches are provided below and further technical details are provided in the subsequent subsections.

The iris modality is well established for adults. However, the existing algorithms in literature were designed for adults, and therefore have an underlying assumption of complete cooperation of the subjects whose irises are being captured. However, children who are very young do not understand and follow instructions. They do not cooperate and often do not look directly at the acquisition camera as required. Therefore, while existing hardware and comparison algorithms were used, adjustments to the preprocessing algorithms had to be added in order to effectively segment and acquire the iris pattern from infants.

The ear modality is very new. There are no commercially available systems or standards as yet. For this modality, the novelty was in applying existing adult ear comparison algorithms from literature to children.

The fingerprint modality is also well established for adults. However, there currently exists no commercially available solutions for children. At the time of embarking on the endeavor of collecting fingerprints from infants, we determined that a higher resolution was required, compared to existing devices which were detailed in the literature.

Additionally, all reported devices were contact-based. We decided on a contact-less approach, to overcome the challenges presented by the soft and pliable nature of an infant's skin. Therefore, the key novelty was in using a contactless, high-resolution device. Once the fingerprints were acquired, software algorithms were developed to process the images and convert them into a format which is compatible with existing contact-based fingerprint comparison software.

The comparison of contactless fingerprints is also an ongoing challenge for adult fingerprints in literature. While the proposed contactless fingerprint recognition solutions for adults in literature often choose a non-standard comparison approach, we chose the approach of making the processed images backward compatible with existing software packages which comply with international standards for fingerprint minutiae feature extraction and comparison. This would allow easy and effective integration of the new developed technology into any existing standardised and established fingerprint recognition systems, which may already be part of large-scale enterprise architectures with databases consisting of millions of users. The backward compatibility will therefore allow for great acceptance and easier adoption of a new technology.

The following subsections go into further detail of the implementation of the chosen approaches for each modality.

Table 1. A summary of the contributed components for each modality

	Iris	Ear	Fingerprint
Acquisition	Iritech IriShield BK 2121U Scanner-II (Developed for adults, applied to infants)	Logitech HD 1080p WebCam (Previously used for adults, now applied to infants)	Prototype 2500dpi camera (first use for acquiring infant fingerprint)
Image processing	Literature algorithm for adults with adjustments applied to infants	Literature algorithms for adults applied to infants	Developed new algorithms
Comparison	Literature algorithms for adults applied to infants	Literature algorithms for adults applied to infants	ISO compliant software for adults applied to infants

A. IRIS

1) IRIS: ACQUISITION METHODOLOGY

The acquisition of iris images were performed by collecting three images of both eyes of each child. The Iritech IriShield BK 2121U Scanner-II was used to collect the images. An example of this device and samples of output images are shown in Figure 3.

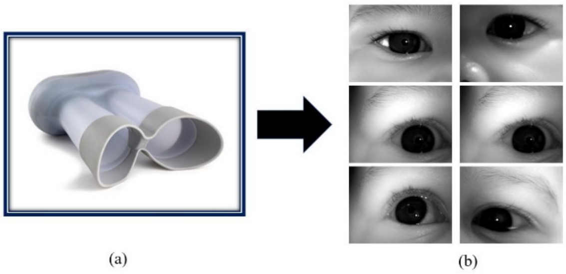

Figure 3. **A picture of (a) the iris scanning device used and (b) samples of output images from different children**

2) IRIS: DATA ANALYSIS METHODOLOGY

These images that were collected from the children might have been of poor quality due to the capturing device used. The reason is the device is not designed for capturing iris biometrics from very young children. Additionally, the youngest children could not understand and fully cooperate during data capturing.

The first step was to discard these low-quality images from our database. These were images with insufficient iris information available, such as the images shown in Figure 4. Such images are due to the sleeping nature of young children and lack of cooperation during iris image capturing. Samples of the remaining, accepted images are shown in Figure 5. The number of accepted and rejected images were used to calculate the failure to acquire rate.

The second step was to apply Daugman's iris recognition to the sifted images, however, a few changes were added. The reason for this is that the sifted images have differences to adult iris images that affect the algorithm. These differences include poor illumination, more variability in pupil size and fewer eyelashes for the younger children.

The the following adjustments were added to address these differences. First, normalized the pixel intensity of the images. Second, relaxed the pupil radius parameter in the iris detection algorithm. Third, removed the occlusion as the lack of eyelashes in the younger children causes the occlusion to cover usable iris regions.

After these adjustments, the Daugman's iris recognition algorithm was applied in a verification simulation as summarized in Figure 7. This method utilizes the Daugman's operators to segment the iris region, with an example in Figure 6. Then uses a rubber-sheet model to normalize the iris region to a uniform rectangular form.

Figure 4. **Noisy iris images during capturing due to uncooperativeness**

Figure 5. **Samples of manually sifted images that have usable iris features but with some noise**

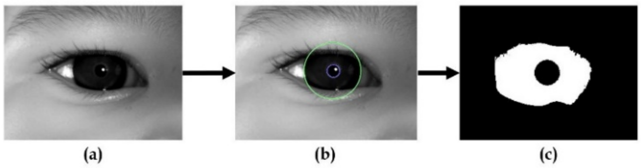

Figure 6. **Iris Image Segmentation Process: (a) Shows a raw input iris image, (b) shows localization of the iris and the pupil regions and (c) shows the segmented iris region without the rest of the eye region.**

The 2D complex Gabor filters were then used to encode the rectangular iris patterns by means of phase modulation. The process is repeated across the iris region resulting in the 2048 bits iris feature template. The iris template was compared to another stored iris template using the normalized Hamming distance. The details of Daugman iris recognition algorithm can be found in [32], [34], [36], [74], [75].

The final step was to calculate the performance of this approach. The equal error rate was used as a performance measure. The results from the data analysis are shown in Section IV.

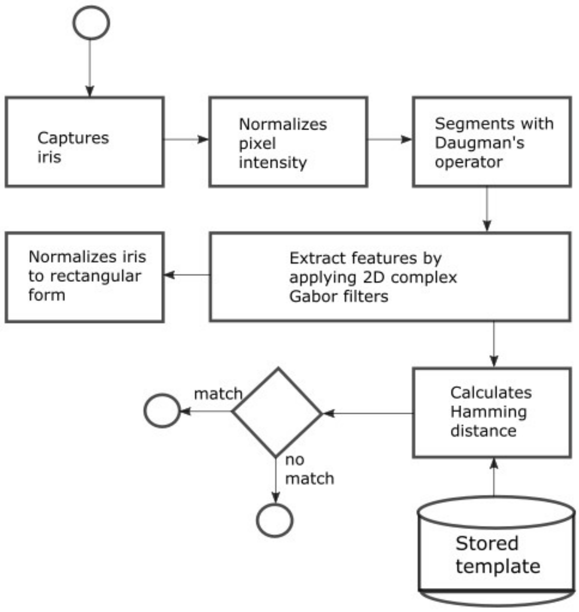

Figure 7. **A flow diagram, illustrating the steps required to process and compare the iris images**

B. EAR

1) EAR: ACQUISITION METHODOLOGY

The acquisition of 2D ear images was performed by collecting photographs for both left and right ear images from children. A 1080p LogiTech webcam was used, which provides 2MP images for the capturing of the images from participants. The distance between the subject and the camera was not considered during the acquisition. The algorithms which were applied are invariant to distance, as long as the features of the ear are clearly visible.

2) EAR: DATA ANALYSIS METHODOLOGY

Ear images captured using a standard camera can be affected by the presence of background, such as skin, hair, and accessories. Therefore, it is important that the ear is located and segmented from the initial ear image. To perform the ear segmentation, a method based on the active contour model has been developed. Active Contour models were first introduced in 1988 by Kass et al. and subsequently gained popularity [77]. Kass et al. described active contour models as a method to search for nearby edges and localize them accurately. This method includes several stages as shown in Figure 8. After capturing a 2D image with an ear, the image is pre-processed to reduce the effect of noise and illumination. Then, the initial active contour is initialized by locating the region of the ear on the received image. In the end, the active contour model is applied to localize the shape of the ear.

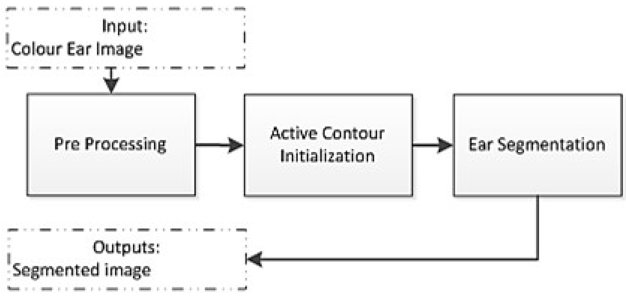

Figure 8. **Ear Segmentation process**

The pre-processing is performed by first detecting the skin region because the ear exists in this region. Non-skin regions are then removed from the segmented image. However, some young children do not have much hair on their heads. This results in the segmented skin region containing some hair. Therefore, there is a need to remove hair by replacing hair pixels with the nearest skin pixels. After removing hair pixels, edges are detected using canny edge detection. The ear is detected from these edges Since an ear contains contours, the region with the ear will contain many small curves that represent the ear. Even if non-ear regions contain curved edges, the concentration differs from the region of the ear. The original ear image is cropped using the region of an ear and the initial contour is estimated using the boundary region of the ear region. This process is shown in FIGURE 9.

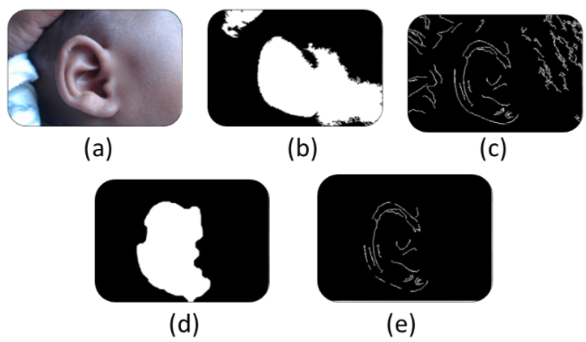

Figure 9. **Representation of a) original image b) detected skin region c) detected edges d) detected ear region, and e) detected edges**

Once the region of the ear is detected, the boundary of the region is computed in such a way that the initial contour can be estimated and the ear image can be segmented. Five different shape methods have been tested to estimate the initial contour, namely, circle, rectangle, corner curved rectangle, ellipse and ear-region boundary. While these methods work, some depend on how edges are presented. For example, the ear-region boundary method lacks accuracy if edges are not connected. It has been observed that if we generate a mask of a circle shape around the region of the ear, the results are better than other methods of masking. This is illustrated in Figure 10.

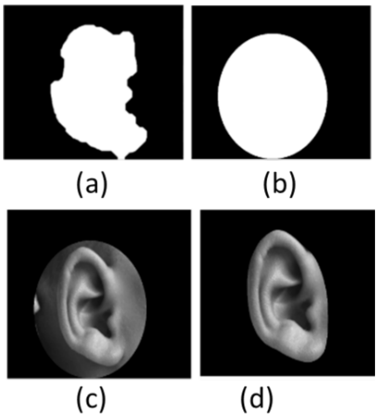

Figure 10. **Representation of segmented ear region using snake model a) mask of a detected ear region, b) initial snake as fitted as a circle, c) ear region with initial snake and d) cropped ear region after applying snake model.**

Features were extracted using the Histograms of Oriented Gradients (HOG) [78]. This type of feature was selected because it has been presented as method which is less affected by the illumination effect [79] [80].

Extracted features are represented as a vector with histogram values computed from the image. During comparison, the Hamming distance is used to compare two vectors of features.

C. FINGERPRINT

1) FINGERPRINT: ACQUISITION METHODOLOGY

Based on the study of related work as discussed previously in Section C, a prototype infant fingerprint acquisition device, as shown in Figure 11, was designed. This device achieves a resolution of 2500dpi, a maximum capturing area of 12mm x 16mm, with visible white light LED ring illumination, and acquisition of contact-less fingerprints in RGB color space. Attachments of various sizes were built to acquire fingerprints at different ages. The purpose of the attachments is to keep the finger steady and open during the acquisition, and to deal with an infant's tendency to close their fingers into a fist. The openings in the attachments allow the acquired area to be contact-less, which prevents smudging and distortion which occur with contact-based acquisition systems. As a note on differentiating terminology, the device is contact-less but it is not touchless, since some part of the finger, which is not acquired, is touching the device during acquisition.

Once the fingerprints are acquired, they are converted into a greyscale image using image processing algorithms using the steps as described below and illustrated in Figure 12 and Figure 13:

1. Background removal: When a photograph of a finger is captured, this picture will contain some background information. The fingertip has to be isolated from its background. This is achieved through colour-based background segmentation.
2. Scale correction: The images can be captured at different resolutions, all higher than the standard 500 dpi. Therefore, the images are scaled to a similar number of inter-ridge pixels than fingerprints from adults captured at 500 dpi. Although this produces fingerprints of children at a resolution higher than 500 dpi, the images will be compatible with commercial fingerprint Software Development Kits (SDKs).
3. Enhancement: The finger photograph that the device captures is a colour image of a finger. It is not in a usable state for fingerprint recognition. The fingerprint pattern still needs to be extracted from the picture. To do this, the colour image must undergo several image enhancement techniques in order to extract the fingerprint pattern. Such techniques include contrast and illumination correction, noise filtering and sharpening. The final usable fingerprint is presented in the Wavelet Scalar Quantisation (WSQ) format, which is the FBI standard for fingerprint images and is accepted by all International Organisation for Standardisation (ISO) compliant fingerprint technologies.
4. Quality Estimation: Since infants in general are uncooperative, it is expected that sometimes the images which are captured will not be of sufficient quality to be usable for verification. For this reason, the the National Institute of Standards and Technology's Fingerprint Image Quality (NFIQ) scoring method was used to assess the usability of a finger image that has been captured. All images with quality levels of 1-3 were included.

At this point, the image is now compatible with existing commercial off-the-shelf minutiae extraction and comparison software, such as the Secugen SDK[81]. Performance measures can then be calculated. This process is illustrated in Figure 12.

For the purposes of performance comparison, fingerprints were also captured with a standard conventional contact-based fingerprint scanner with a resolution of 500dpi. To maximize the performance of this method, a continuous stream of fingerprints was captured, and the fingerprint quality of each frame was measured. The infant's fingers were moved around on the device and the images with the highest quality scores were recorded.

Figure 11. **The contactless infant fingerprint acquisition device with different sized attachments to cater for varying sizes of children's fingers**

Table 2: Summary of participants and amount of data collected for each modality

Age Group	Age Range / days	Number of Participants	Number of Iris Images	Number of Ear Images	Number of Fingerprint images (prototype)	Number of Fingerprint images (conventional)
Group 1	age ≤ 112	12	60	54	223	41
Group 2	112 ≤ age ≤ 168	30	78	127	271	41
Group 3	168 ≤ age ≤ 365	102	216	265	694	71

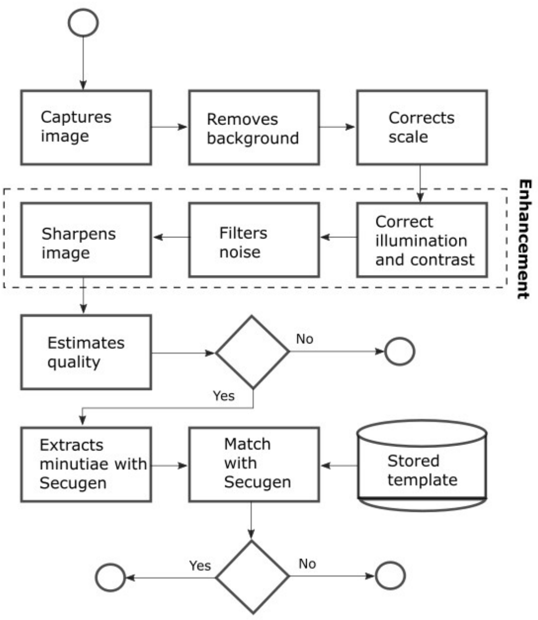

Figure 12. **A flow diagram, illustrating the steps required to process and compare the contactless fingerprints**

Figure 13. **An illustration of the process from (a) the acquisition of the image of an infant's fingerprint, to (b) image processing to convert the fingerprint into a format which is compatible with commercial off-the-shelf comparison software, to (c) the extraction of minutiae points from the fingerprint.**

2) FINGERPRINT: DATA ANALYSIS METHODOLOGY

The aim of the data analysis is to assess the effectiveness of the prototype fingerprint-acquisition hardware and software system in comparison to a standard fingerprint scanner.

The data analysis was further divided into two stages. Stage 1 determined the image quality under different scenarios, whereas as Stage 2 determined the error rates after simulating fingerprint verification under different scenarios. The following steps were adopted to achieve this:

- Collect three impressions from each finger.
- Automated conversion of the photographic fingerprints with image processing algorithms into a format which is compatible with commercial off-the-shelf fingerprint processing software.
- Perform the quality assessment (Stage 1). The NFIQ quality score [82] was used.
- Perform the verification simulation (Stage 2). Commercial fingerprint feature extraction and comparison software, such as the Secugen SDK [81] was used

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In the analysis of the experimental results, we utilized the standard error rate measures, Equal Error Rate (EER) and Failure to Acquire (FTA) to measure the performance. In this section, the datasets, quality analysis, and performance analysis are reported and discussed for the iris, ear, and fingerprint modalities, respectively.

A. *DATA COLLECTION*

Data were collected from volunteer participants at a public clinic. Due to challenges that will be discussed in the Lessons Learned section, data was collected from participants in a single session. The participants were split into 3 groups, based on the vaccination schedules which determined at what age the participants were present at the data collection location. The first group was participants of age 16 weeks and under. The second group were participants above 16 weeks and below 6 months. The third group was participants older than 6 months and younger than 1 year. The number of participants and images are summarized in Table 2.

While the same participants were used for each modality, it was not always possible to collect biometric data from all of the participants in all instances. This was due to some babies becoming restless and crying and others falling asleep. These challenges are discussed further in the Lessons Learned section. While there is sufficient data to assess each modality individually, the inconsistencies which were created in collecting data from infants, limit the ability to assess a multimodal system at this point in time. The following sections will discuss the performance assessments of the individual modalities.

A. IRIS

1) IRIS: DATA

In this study, iris images from 56 participants under the age of 1 year were collected, with the youngest participant being 6 weeks old. From each participant, 3 impressions from each eye were taken. However, due to the inability of babies to always adhere to instructions, less than 3 impressions were obtained in some instances. This provided a total of 132 unique eyes and a complete dataset of 354 iris images.

The participants were split into 3 age groups as shown in Table 2.

2) IRIS: DATA CLEANING AND QUALITY ANALYSIS

Acquiring the iris images for children under a year are difficult. The infants at this age were unable to follow instructions. Furthermore, some of the infants were afraid to look into the scanning device and resisted acquisition, while others closed their eyes when bringing the device near their faces.

This resulted in a failure to capture iris images or capturing images in which the iris was not visible. Data cleaning was performed manually by removing all the images where the iris was not visible. Only 144 of the possible 354 images were usable. For a more detailed overview of the collected, visible iris images and failure to acquire (FTA) rate per age group see Table 3.

Furthermore, the images that were acquired with visible irises might not have been of good quality. Figure 14 illustrates three possible cases. These problems affect the performance in iris recognition.

3) IRIS: PERFORMANCE ANALYSIS

The performance of the collected data was measured based on the equal error rate (EER) calculated for different verification scenarios.

The results of the EERs are shown in Table 4. The EERs are significantly higher than for adults.

Table 3. **The acquisition rate of usable iris images for each age group.**

Age Group	Collected	Good Quality	Acquisition rate (%)	FTA
Group 1	60	12	20.0	80.0
Group 2	78	30	38.5	61.5
Group 3	216	102	47.2	52.8

Table 4. **The equal error rate (EER) for the iris comparisons in the different age groups.**

Age group	Equal Error Rate:
Group 1	33.33
Group 2	15.00
Group 3	26.34

(a) (b) (c)

Figure 14. Samples of **low-quality iris images that were captured, where the iris is visible, with a) partially open eyes, b) bad illumination as the eye is not in the centre of the image, and c) infant looking away from the camera.**

B. EAR

1) EAR: DATA

Ear images were acquired using a Logitech HD 1080p WebCam camera. Ear images were successfully collected from 71 participants, from the age of 6 weeks and upwards. Six ear images were captured from each participant, with three of the left ear and three of the right ear.

2) EAR: DATA CLEANING AND QUALITY ANALYSIS

One of the advantages of using ear recognition is that it is easy to capture ear images. Shown in Table 5 is the summary of the data collection outcome per age group, which indicates a high acquisition rate in comparison to the iris and fingerprint modalities for young children. However, there were a few cases where children were scared of the camera and they did not allow their ear images to be acquired. In such cases, researchers stopped the acquisition process. In total, 446 ear images were collected. These are broken down into age groups as shown in the "Collected" column in Table 5. However, not all images that were collected were useful to the study, as some were affected by pose variation, and low image quality due either to being out of focus or due to high brightness. As a result, only a total of 409 images were of sufficient quality for comparisons. These are broken down into age groups as shown in the "Good Quality" column in Table 5. Hence, the total number of images that were compared resulted in 553 genuine comparisons and 3314 impostor comparisons.

3) EAR: PERFORMANCE ANALYSIS

During the comparison, HOG features extracted from two ear images were compared by calculating the similarity between two feature sets using the Hamming distance method. The results are reported using the Equal Error Rate (EER) which is computed based on the calculated Hamming distance. The results are represented by age group as shown in Table 6. The determined overall Equal Error Rate is 7.64%. The EER value can be affected by pose variations, when ear images of the same participant, which were captured in different instances, are compared.

The achieved EER values indicate the performance of ear recognition system on the collected data. This performance is affected by the quality of ear images caused by the environment (light) and pose variation.

Table 5. The acquisition rate of usable ear images for each age group.

Age Group	Collected	Good Quality	Acquisition rate (%)	FTA (%)
Group 1	54	48	88.9	11.1
Group 2	127	120	94.5	5.5
Group 3	265	241	90.9	9.1

Table 6. The equal error rate (EER) for the ear comparisons in the different age groups.

Age group	Equal Error Rate
Group 1	7.04%
Group 2	9.26%
Group 3	6.58%

C. FINGERPRINT

1) FINGERPRINT: DATA

In this study, fingerprints from 66 participants under the age of 1 year were collected, with the youngest participant being 6 weeks old. From each participant, 3 impressions from 6 fingers were taken, i.e. 3 impressions each from both thumbs, both index fingers and both middle fingers. This provided a total of 396 unique fingerprints and a complete dataset of 1188 total fingerprints using the prototype contactless fingerprint scanner.

As a benchmark for comparison, fingerprints were also collected with a standard 500dpi fingerprint scanner, the Futronic FS-88. However, due to the restless and uncooperative nature of babies, data collection had to occasionally stop before all the fingerprints could be collected. Thus, the number of fingerprints collected using the conventional scanner were less than those collected using the contactless fingerprint scanner.

The participants were split into 3 age groups as shown in Table 2.

2) FINGERPRINT: DATA CLEANING AND QUALITY ANALYSIS

The NFIQ image quality score [82] is based on a fingerprint's performance in a verification system. Although it was not designed for infants, it can still provide information regarding the quality of the prints. The scores range from 1 to 5, with 1 being the best quality and 5 being the worst. A comparison of the image quality scores for the prototype scanner and a standard 500dpi scanner are shown in Table 7. This comparison shows that, overall, fingerprints collected with the prototype scanner produce a better average NFIQ score than those collected from standard scanner across all the age groups which were studied. The NFIQ scores for the fingerprints collected with the prototype system also have a lower standard deviation than the NFIQ scores for the fingerprints collected with the standard scanner.

Table 7. Average NFIQ scores and standard deviation for the different age groups

Age groups	Prototype	Standard
Group 1	2.93 ± 0.98	4.13 ± 1.53
Group 2	3.23 ± 1.09	4.16 ± 1.51
Group 3	3.37 ± 1.11	4.45 ± 1.14

Based on the number of acquired fingerprints per participant and the quality scores, and acquisition rate was determined with an NFIQ quality threshold set at 3. In other words, fingerprints with a quality between 1 and 3 were regarded as being of acceptable quality to use in comparisons, while fingerprints with a score above 3 were regarded as low quality and a failure to acquire. Thus, the successful acquisition rate for fingerprints with the prototype scanner was 75%, while the successful acquisition rate for fingerprints with the standard scanner was nearly half of this at 40%. This shows that the prototype scanner is more effective at acquiring fingerprints from children compared to a conventional fingerprint scanner. Figure 15 shows a comparison between infant fingerprints obtained using a standard scanner and the prototype system. The fingerprint obtained from the standard scanner is smudged, with insufficient pixel density to clearly resolve the ridges and valleys of the fingerprint. Conversely, the fingerprint obtained using the prototype system provides sufficient pixel density to resolve the ridges and valleys. Minutiae points are visible and can be used for comparisons.

A breakdown of the acquisition rate for each age group with the prototype system is shown in Table 8. The reduction in acquisition rates for the older age groups may be due to partially captured fingerprints, where an insufficient area of the fingerprint was captured. Partially captured fingerprints occurred when fingers may have been too large for the capture area of the prototype scanner which was used.

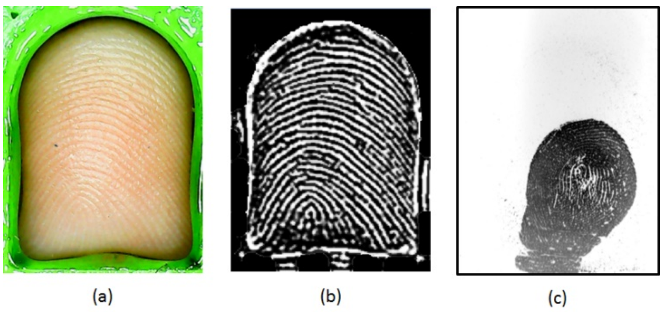

Figure 15. A comparison of fingerprints collected from a 10-week-old child using the prototype system and a standard scanner. (a) The fingerprint obtained with the prototype; (b) the fingerprint from (a) after processing; (c) the same fingerprint obtained using a standard scanner.

3) FINGERPRINT: PERFORMANCE ANALYSIS

The performance of the collected data was measured based on the equal error rate (EER) calculated for different verification scenarios.

The results of the EER comparisons are shown in Table 9. For the youngest age group, Group 1, it may appear that the standard scanner has a better EER. However, it must be noted that most of the fingerprints that were collected with the standard scanner for this age group were of too low a quality to be used in the comparisons. The standard scanner had a high rate of failure to acquire and, therefore, there are an insufficient number of fingerprints to state the standard scanner's EER score with confidence in the precision. The prototype scanner performed better than the conventional scanner for all age groups below 1 year.

This confirms our hypothesis that using a higher resolution (2500dpi) and a contactless scanner will produce better match scores compared to a standard 500dpi scanner. While these scores are comparable to the latest results from high resolution contact-based scanners [64], these performance scores still fall short in comparison with adult systems.

There are several possible reasons for the lower performance, which could be addressed in future iterations of the system. These are discussed in Section E. Lessons Learned.

Table 8. The acquisition rate for each age group using the prototype system

Age group	Collected	Good quality	Acquisition rate (%)	FTA (%)
Group 1	223	191	85.7	14.3
Group 2	271	204	75.3	24.7
Group 3	694	493	71.0	29.0

Table 9. The equal error rate (EER) for the same comparisons by both scanning devices in the different age groups.

Age groups	Prototype (no. comparisons)	Standard (no. comparisons)
Group 1	15.56% (360)	4.76% (42)
Group 2	15.45% (382)	32.0% (50)
Group 3	23.03% (890)	23.86% (88)

D. COMPARISON OF MODALITIES

In this section, we compare the various modalities and their effectiveness in different age groups, so as to make recommendations for the future.

A summary of the improvements over literature and their shortfalls, are summarised in Table 10.

The acquisition rates are shown in Figure 16.

The ear has the highest acquisition rate. This modality is the easiest to collect as the ear pattern is easily visible with the human eye and can be captured with a simple camera, without any need for contact or active interaction with the child. The main challenge occurs when children move around excessively or want to turn their head to look at the camera. With assistance from the parents to keep the child's head still, this challenge is overcome.

The fingerprint has a similarly high acquisition rate. The decline in acquisition rate as the children grow is due to the limited capturing area of the current device. This leads to partial fingerprints which do not have an overlapping area. A more ergonomic design will also allow for faster capture with children who move their fingers away from the camera too quickly.

The iris has a very low acquisition rate in the younger age groups. This is because infants cannot understand instructions, while the iris scanner requires a high level of compliance, where the individual is required to look directly at the camera. Some children were also asleep, and their eyes were closed. However, as children grow older, they begin to understand instructions and stay awake for longer periods. This allows for a higher acquisition rate for irises with older children.

The EER for each modality across the various age groups is show in Figure 17. The ear modality has the lowest EER. The higher EER for the iris and for the fingerprints can, once again, be attributed to the lower compliance of infants and limitations in the design of the capturing device, respectively. However, it should be noted that, since an individual has fewer irises and ears than they have fingers, the overall dataset size for irises and ears are smaller, which may affect the precision of the results.

Based on the analysis of these results, we recommend that fingerprints and ears can be used in a multimodal system for infants from birth. On the other hand, until a technique is developed to acquire irises more consistently from younger children, iris recognition would be more reliable in biometric systems which cater for children who are 1 year old or older.

Moving forward, the following tasks are envisioned. The acquisition device for fingerprints must be refined. A larger dataset of all the modalities should be collected simultaneously to allow for an analysis of multimodal fusion techniques. The child participants should have their biometrics captured at regular intervals to assess the ability to match these traits across different ages.

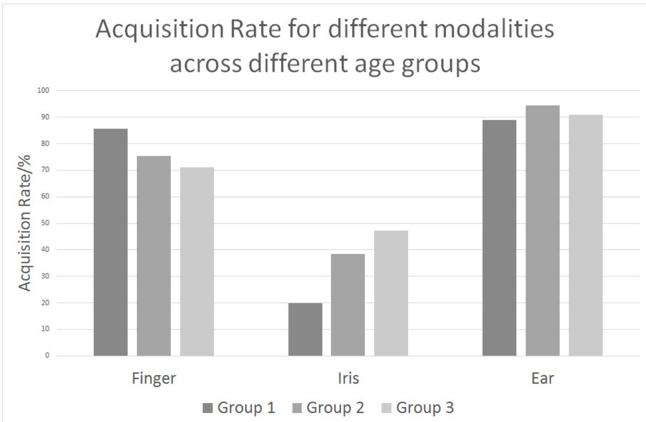

Figure 16. A comparison of the acquisition rate for each of the modalities across the three age groups

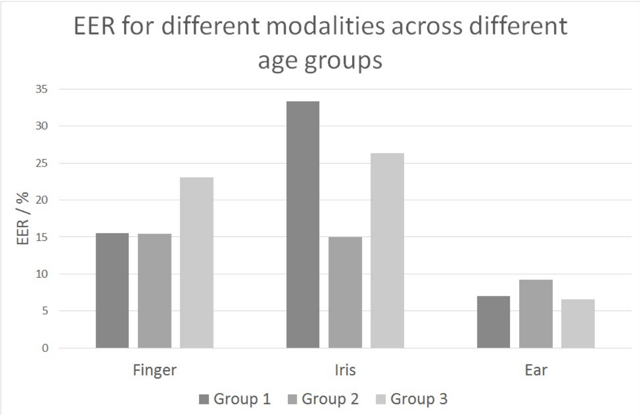

Figure 17. A comparison of the EER for each of the modalities across the different age groups

E. LESSONS LEARNED

To conduct research into infant biometrics, data must be collected from children at regular intervals over an extended period of time. A longitudinal data collection would allow the assessment of change as children grow over time [3]. While initial data was successfully collected, many challenges were faced.

In an ideal world, much of the interactions between the research group and external stakeholders would be handled by a public relations manager. However, due to limitations of funds, the responsibility of public relations often falls on the shoulders of researchers, who usually have no public relations training. The following discussions should help prepare researchers for a myriad of scenarios, which they may not expect when embarking on data collection from participants among the general public, and children in particular. This discussion should assist in considering, reducing and mitigating risks involved with data collection from infant participants, and increase the chances of success in similar projects.

This was the first attempt of this research group to embark on a large longitudinal study with human participants in public environments, and dealing with children in particular. It is a situation which researchers trained in mathematical sciences are not prepared for. To the authors' knowledge, there are no comprehensive publicly available guidelines for data collection in this context. Incomplete reporting of studies involving children is a known challenge across research fields, including the health sector, where reporting guidelines and protocols already exist [86]. Infancy researchers acknowledge that, while there is a high complexity when conducting research with children, there is a lack of transparency in the details, successes and failures of applied research processes [87].

Due to this lack of transparency and incomplete reporting in prior research, many unforeseen circumstances were encountered, even with prior planning. Many of the responses and mitigation strategies were reactionary to make the most of less-than-ideal circumstances. For this reason, records of results of different approaches are more qualitative and observational, rather than quantitative. However, it is hoped that the transparent record of these experiences will sensitise future researchers who embark on similar endeavours to prepare more thoroughly, and that it may set an encouraging example for other research groups to share their experiences in a more transparent manner as well. This may allow for smoother research, and faster and higher quality outputs in the future, with regards to research in the new and growing space of biometric recognition of children, and infancy research in general.

1) DEVICE DESIGN

If technical devices are to be used, these should be packaged in a non-threatening manner. Child-friendly designs and appearance will reduce the reservations of parents and attract children to the study and help hold their attention.

If the device makes contact with participants and is used with young children in medical environments, compliance with biocompatibility standards must be included in the design[89].

Based on the data collected thus far, several key areas of software and hardware have been identified for improvement of the prototype fingerprint scanner.

In terms of hardware, one of the main challenges is the limitations with openings of set sizes. If the opening is too large, the child's entire finger will go through, which makes acquisition impossible. If the opening is too small, only a partial fingerprint will be captured. Partial fingerprints are not representative of the entire fingerprint. When different partial regions are acquired in different instances for the same finger, an insufficient overlap will reduce the ability to successfully compare two impressions from the same finger.

Specular reflections from white ring lighting often affects the ability to clearly see some regions of the fingerprint. This is illustrated by samples in Figure 18. Based on work in literature [66][71][72][73], the use of blue lighting with polarized filters may reduce reflections and allow for a clearer fingerprint. Another alternative is the use of optical coherence tomography (OCT) which could acquire the subsurface fingerprints in a contactless manner and is invariant to moisture and reflection on the surface of the skin [83][84][85]. However, further improvements in speed, depth of field and component costs would need to be made before OCT is suitable for mass production and usage.

In the study performed by Basak et al. [11], fingerprints from children 18 months and older were collected with a conventional adult scanner. While the success rate for comparisons with a single finger were low, performance was improved by score level fusion of all 10 fingers. Once a larger dataset of individuals is collected, a similar approach can be tested for younger infants, using data collected with a contactless fingerprint acquisition device.

Table 10. **A summary of the improvements which were investigated and reported on, and the shortfalls of the methods, which require further research and investigation**

Modality	Improvements over literature	Shortfalls
Iris	The main contribution was testing an existing algorithm on children and seeing how it performs. Additionally, the team had to add image normalization to help deal with the uncooperative nature of the children.	The main shortfall is the binocular device, where some children were afraid to look into the device. Another shortfall is limited data to assess the iris as the children grow.
Ear	Similar to the iris, for the ear, the main contribution was testing an existing algorithm on children and measuring the performance.	The main shortfall with the ear, similar to iris and fingerprint, is testing over a period of time to see how it is affected by growth.
Fingerprint	Fingerprints of younger children have previously been tested. Therefore, this paper approached the challenge differently. The main contributions with the fingerprint are with the acquisition device: that it is a contactless acquisition; and that it acquires fingerprints at a high resolution. Other contributions are the interoperability with existing matching software and comparison to the standard contact-based scanners.	The main shortfall is that the device acquires images over a limited area, which results in partial fingerprints in some cases. Additionally, as mentioned for other modalities, data could not be captured longitudinally to assess the effect of growth.

Figure 18. **Samples of infant fingerprints which displayed specular reflection under white LED ring illumination.**

2) CHOOSING DATA COLLECTION LOCATIONS

Once ethical clearance has been obtained, individual locations may be approached for permission to use their facilities. For continuous longitudinal access to children of varying ages, such locations may include hospitals, clinics, day care centres, schools and extra-curricular clubs.

An exhaustive search may need to be performed to find suitable facilities, especially in developing countries with limited funds and resources. Thoroughly compiled stakeholder registers and stakeholder engagement plans may help the process [88]. Some places are willing to assist but do not have space or suitable time. Others may be hesitant to be involved.

Space is often limited, especially in the context of public facilities in developing countries. This must be taken into account when approaching facilities for use of their space. Many cannot accommodate researchers. Care should be taken that equipment is compact and requires minimal space. Tables and chairs may need to be sourced by the researchers as the centres often do not have enough to spare. Those costs to purchase and transport this equipment to and from the facility should be factored into budget planning.

The effect of weather should be taken into account, especially if researchers performing the data collection have to be stationed outdoors, either due to the nature of the data collection or due to space limitations. Cold, rain, or extreme heat may cause discomfort, which in turn may discourage people from attending data collection session and reduce the number of participants who are available in poor weather conditions. Uncomfortable weather conditions may also dampen the enthusiasm of researchers to collect data. Data collection should be aligned with the optimal local seasons for comfortable weather when working in environments which cannot provide air conditioning.

3) ENGAGING WITH CHILD PARTICIPANTS

Interactions with children vary with age. For children below the age of 6, data collection is much more effective when the parents are physically present after providing consent. Their presence makes the children feel safer to interact with researchers who they may view as strangers; and the parents feel comfortable when they can witness how the data collection process is conducted and assist in the data collection. For these reasons, data collection at clinics was much more productive, efficient and successful than at day care centres.

However, some children attend the clinics for treatment which involves injections, such as vaccinations. Receiving an injection from the clinic's nurses immediately prior to data collection may then make the children uncomfortable and temporarily distrustful of other strangers, such as data collection researchers. In such situations, it is better to collect the necessary data before the children see the nurses for their vaccinations.

It was the experience of the research team that children above the age of 6 years are generally more curious and bolder. They feel comfortable interacting with researchers when a teacher is present and do not need parents nearby. In the scenario of collecting data with electronic devices, after the older children are shown how to use a device, they immediately show interest and excitement and are also able to handle the device on their own without any assistance.

If the research requires data collection from very young children, such as newborns, then medical professionals should be included in the recruitment and data collection process. Such professionals are better trained at dealing with babies and will be more trusted than scientific researchers by new parents.

4) LONG-TERM DATA COLLECTION

In the case of a longitudinal study, the repeat availability of participants must be considered [22]. Depending on the hosting facility, availability schedules may not fit the ideal data collection intervals, and researchers may need to compromise and be flexible to prioritise repeat data samples from participants over a regularly spaced schedule. Additionally, it should be expected that repeat participants may reduce over time, as people relocate or lose interest in contributing to the study. The movement of children from day care centres to primary schools and then to high schools over a number of years should also be taken into consideration. Researchers may need to record the contact details of parents. Researchers could then contact the parents via phone numbers and email addresses to arrange times for repeat data collection. In environments with low English literacy, multilingual approaches should be considered. In many countries, it is illegal to provide monetary incentives for participation in research studies. In such cases, researchers need to impress on the importance and social value of continuous voluntary participation in longitudinal studies. Researchers should factor in a large portion of time to follow up with participants at the required intervals, and should factor in the possibilities of a high drop-out rate, if participants have to put in too much effort to attend data collection sessions to continue contributing to the study.

5) PARTICIPANT DEMOGRAPHICS AND LOCATION CHOICE

In an ideal scenario, a balanced representation of data would be obtained. However, in the real-world scenario, access may be obtained to facilities where there is a bias in demographics which may skew representation. For example, representative participants of certain demographic factors such as age, race or economic groups may be more present than others. When collecting a dataset for the development of a biometric system, the prevalence of certain biometric traits, such as ear lobes for ear biometrics, may be affected by some of these factors. Thus, the dataset which is collected will influence the performance of the final system. Therefore, the dataset should be representative of the final population which it is meant to serve. The distribution of population demographics should be taken into account when choosing locations for data collection.

V. CONCLUSION AND FUTURE WORK

We presented biometric systems for recognising infants by their fingerprints, irises and outer ear shape. Each of the modalities have different strengths and weaknesses.

It has been found that ear biometrics are easy to acquire from birth and existing algorithms which were developed for adult ears do work for infants' ears as well.

We have shown that is it possible to develop a hardware device to acquire fingerprints from infants, with participants as young as 6 weeks of age, and record infants' fingerprint information in a format that is compatible with existing fingerprint comparison software.

We have also shown that iris biometrics can be used to successfully match individuals from as early as 6 weeks and that the acquisition rate improves as children become older.

Recommendations were provided on ways in which to combine these modalities in future work, to create more robust and more accurate biometric recognition systems for infants and to extend these systems for effective use from birth to adulthood. Further work will include improvements on the acquisition hardware and the multimodal fusion of biometrics to create strong, flexible and more robust biometric recognition system for infants. The introduction of different biometrics at different ages in various use-cases will be investigated.

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