Fingerprint Biometrics From Newborn to Adult: A Study From a National Identity Database System

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Abstract—In this work, we evaluate the use of fingerprints to identify people from a very young age. Although it is well known that fingerprints are stable all along life, and even before born fingerprint patterns are fully developed, automatic identification (or comparison) systems are developed generally for adult fingerprints. Our interest is not only to study the feasibility of using child fingerprints for automatic identification but to determine if that is possible with the existing software and hardware. There are two related questions that we do answer in this work. First, starting at what age are digitally acquired fingerprints good enough for automatic comparison. Second, what is the performance when comparing fingerprints from children against fingerprints from adults. In order to answer these questions, we have run a set of experiments on a database composed of more than 200K fingerprints from approximately 134K identities. We show that, after applying a growth factor to scale minors fingerprints to an adult size, good accuracy can be obtained from ages starting at one year old, and that fingerprints of children and adults can be compared without a significant loss of accuracy (with respect to adult vs adult). We consider this study extremely useful for both researchers and decision makers, as it is a testimony that even without additional developments, fingerprints from children can be used for automatic comparison on real scenarios.

Index Terms—Biometrics, fingerprint recognition, ageing, children, fingerprint quality.

1 Introduction

THE aim of the present work is to analyze the use of child fingerprints as a valid biometric trait in the context of identity verification. Although the permanence of fingerprints throughout time is well known (towards the end of the nineteenth century, Sir William Herschell published the first preliminary work in relation to the permanence of fingerprints characteristics over time [1]), our focus is not placed on whether real fingerprints from children are indeed stable all along time, but rather if their corresponding digital images, acquired in the conditions of a production system, are good enough to be used in practice. Due to the fact that both the vast majority of the research in relation to fingerprints and the commercial implementation of most AFIS (Automatic Fingerprint Identification System) are implemented and tested on children starting at 12 years of age, very little information exists regarding how these systems perform when fingerprints of children under 12 years old are used. In this work we will focus mainly in fingerprints belonging to children from ages 0 to 12. Therefore, unless otherwise stated, when we mention children, we will be always referring of this age range.

One may wonder what is the interest in studying child fingerprints in the first place. First of all, let us recall that fingerprints are the most used biometric trait for civil identification. Excluding Anglo-Saxon countries (where in general, no National ID system is in place), the vast majority of national identification systems are based on fingerprints. This has a very simple explanation: fingerprints are one of the most permanent biometric traits, and have been acknowledged as such since the very beginning of the twentieth century. Indeed, many countries identify their citizens using this information, and nowadays some of them have fingerprint databases that are over 100 years old. Additionally, fingerprints can be classified in groups, which makes the searching process very simple. In the 1970s, when automatic fingerprints systems started to be implemented, many countries already had fingerprint databases, based on paper forms. Still today, fingerprints continue to be the most used biometric trait for civil identification.

The interest in children identification can be illustrated with several use cases. First of all, as children are part of the population of a country, it makes sense to include them in the biometrics systems that support national ID programs. Several countries are registering their population at an increasingly younger age (Uruguay: since birth, India: 6 years old, Colombia: 9 years old, etc.). But this is not the only reason. As explained in [2], vaccination programs take advantage of identity verification based on fingerprints to prevent double application of the same dose. These two examples serve also to illustrate two different but related problems. In the case of national ID systems where Passports and National IDs are renewed every 5 or 10 years, the main interest is to understand if fingerprints with a 5 or 10 year lapse between acquisitions can be compared with good accuracy. That means that at some point, we will be comparing fingerprints from children with fingerprints from adults. The question to answer here is: *can fingerprints from children be compared with fingerprints from adults, when the lapse time between acquisition is significant (for example, more than 10 years)?*. In the case of vaccination campaigns, the comparison may be done in a much shorter time. In this case, the question is: *since what age can fingerprints from children be used for automatic identification ?*. These two problems can be related to the *age* and the *ageing* effects described in [3]:

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- **Age effect**. *This effect is related to the variations in accuracy between different user groups according to their age, such as children, adults and elderly.*

- **Ageing effect** *This effect accounts for the variations in accuracy due to the increase of the time difference between the reference sample and the probe sample.*

In spite of the interest on child fingerprints as a valid biometric trait, very few systems are suited to work with such data. Although there may be other reasons why it is not widely used, one of the biggest problems that the research community faces is the lack of studies regarding the use of fingerprints from children for automatic comparison. An obvious reason is the lack of systems in the world where fingerprints of minors and adults are acquired together.

In this work, we present an exhaustive study of child fingerprints done with data obtained from the Uruguayan National ID Card and Passports System (a preliminary version of this work was already reported in [4]). All data was collected from the real ID card and Passport application, which is a typical scenario for fingerprint collection. This means that all the data used for this analysis was obtained from real conditions and not in laboratory or ideal conditions. We have sampled the database of several million fingerprints to obtain a dataset of approximately 208K fingerprints (74K pairs of fingerprints), ranging from 0 to 18 year old. In order to answer the two questions presented before, we designed two different experiments. In the first one, we analyzed what is the earliest age at which we can start acquiring fingerprints that can be used for automatic identification (note that we are leaving out of this work the manual comparison that can be done by fingerprint experts). In the second experiment, we analyzed if child fingerprints can be compared with adult fingerprints. In both cases, the objective is to analyze the accuracy obtained using the same hardware and software as the ones used for adults. Thus, we are not including any new hardware, nor we are proposing a new algorithm or process: the only proposed step is to resize the images, due to limitations in some of the fingerprint matchers.

In summary, the contributions of the present work are two-fold. First, we show that fingerprints acquired at very young ages (five years old) can be compared with fingerprints acquired ten years later (and thus, from adults) without any significant loss on accuracy and using the same software and hardware as used for adults. Secondly, we show that when the same software and hardware are used to acquire fingerprints from children as young as one year old and from adults, the system is accurate enough to be reliable. Because all the fingerprint images were obtained from data collected from an ID and passport system, the results can be considered as the expected ones on other production systems (and particularly, in other ID and Passport systems).

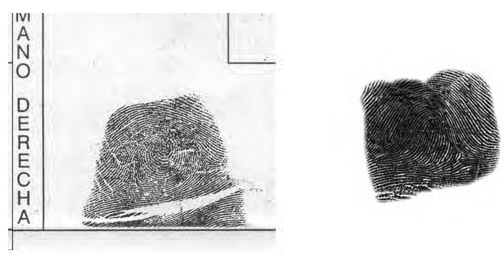
2 Related Work

In recent years, several works were conducted to analyze the suitability of using fingerprints in children for identification purposes [2], [3], [4], [5], [6], [7]. In 2013, a work done by the European Commission was presented [5]. In that work, a database of fingerprints obtained from $2,611$ children (in the 0-12 age range) with 500 dpi scanners were used.This data was acquired by the Portuguese government passport issuance offices. The report concluded that it was difficult to identify children under six years old. In [7], a study was done in a population of 309 individuals ranging from zero to five years of age. The feasibility of using fingerprint to identify children at an early age was reported in that work for the first time: good results were obtained in children older than six months using special scanners of 1270 dpi. Good results were also obtained using standard adult fingerprint scanners of 500 dpi in children that were at least one year old.

One of the most exhaustive and up to date studies in fingerprint ageing has been recently published [3]. In that study, the authors presented the result obtained from a dataset of more than 420K fingerprints from approximately 265K different fingers and from ages 0-25 and 65-98. In the case of minors, the dataset comprised approximately 300K fingerprint images (approximately 100K pairs since some of the fingers have only one acquisition). Although this study is by far the biggest study done on ageing and the effects of age on fingerprints, it does not cover the fingerprints of minors completely. In particular, the group composed of 0 to 4 year olds was treated together, without a detailed analysis of the differences inside that group. For the age problem, the authors reported a very bad performance for children aged 0 to 4: more than 35% of FRR at 0.1% FAR. In the case of the ageing effects, the results obtained for children is not better: more than 20% FRR with a 0.1% FAR when the time between acquisitions is 7 years. These bad results are not in accordance with other results reported before and with our previous work [4]. We can only guess what may be the issue: because most commercial algorithms are not robust to big scale changes, the comparison with small fingerprints gives very bad results. We show that we also faced this problem during this study, and that we have solved it by using a simple scale factor to improve the accuracy of existing software to values comparable to adult ones. The present work can be seen as the continuation of our previous work [4], and also a contribution on the work presented in [3].

3 Description of the Uruguayan scenario

Uruguay is a very special case in relation to civil identity management. As many other countries in the world, Uruguay has a national ID System, which is strongly based on fingerprints. But what makes Uruguay unique is that fingerprints are acquired since birth. And for the purposes of this study, even more important is the fact that this is done since the very beginning of the system implementation, back in the 70s. In 1978, the National Civil Identification Agency (DNIC) was created. The agency is, since then, responsible of issuing national ID cards and passports. By law, parents have 45 days from birth to obtain the identity card of the newborn. Due to the difficulty of matching the fingerprints of newborns (mainly because of low quality), this information is only stored but is not used for identity verification or de-identification processes. When the child is 5 years old, a complete ten fingerprint template is obtained, which is stored as the biometrical attributes of the individual. Due to the fact that this process has been executed since 1978, all natural Uruguayans born before 1973 are actually enrolled with their 5 year old fingers (nearly 2.4 million people in a population of 3.14 million). When an ID document is renewed (which is done every 5 years for minors and every 10 years for adults), an adult fingerprint is generally compared against a fingerprint corresponding to a 5 year old child. Until 2010, all the fingerprints were obtained using ink on paper. As part of the enrollment process, these templates were scanned at 500 *dpi*, segmented on each fingerprint, and stored digitally for further visualization. It was not until 2011 that an AFIS system was installed, which was fed with all those previously scanned fingerprint images. From 2011 until now, the ten fingerprints are acquired using live-scan scanners. See Figure 1 for some examples of the kind of fingerprints images stored in the database.



(a) From 1978 to 2011 (b) From 2011 to present

Fig. 1: Two different types of images that compose the dataset: paper-based (left) and live-scan (right).

4 Protocol Specification

We base our protocol in the two questions we want to answer:

- Question one : with standard hardware and software, starting at what age are fingerprints *good enough* for identification purposes?
- Question two : with standard hardware and software, what is the accuracy of fingerprint comparison between fingerprints of 5-year old minors recaptured 10 years later?

The considerations for each case are described next. Before that, we present the dataset that we have used for all these experiments.

4.1 Dataset

The dataset was chosen in order to tackle the two questions presented above [1]. A total of **16865** identities were selected, where at least a pair of images of the same fingerprint exists. The dataset is then composed of **178843** fingerprint images from **134330** different fingers, with **75262** image pairs. Table 1 shows the distribution of the fingerprint samples in relation to the age of the person. Note the peak on the number of fingerprint images at 5-6 years old. The reason for this peak is the following: in order to perform our study, which is based on fingerprint comparison, we need to have pairs of fingerprints from the same individual. Because the Uruguayan ID document expires exactly at the age of 5, it is highly probable that one of the images in the set will be from this age. In fact, that is the case: nearly 44% of the dataset images were taken from 5 year olds. What is more, most of the fingerprints in the dataset were taken from children under 6. Table 3 shows how image fingerprint pairs are distributed with respect to acquisition age. Finally, we want to highlight another characteristic of the dataset: due to the time lapse between acquisitions, some of the fingerprints were acquired on paper and later digitized (see Figure 1). Table 2 shows how paper-based and live-scan fingerprints are distributed in the dataset. We include some examples of the fingerprint images included in the dataset in Figure 2.

Age	Number of fingerprints
0-1 m	13961
1-2 m	6299
2-3 m	1876
3-4 m	1758
4-5 m	1026
5-6 m	1562
6-12 m	6780
1-2 y	5008
2-3 y	4276
3-4 y	816
4-5 y	20
5-6 y	78426
6-7 y	15332
7-8 y	5150
8-9 y	1272
9-10 y	252
13-14 y	16
14-15 y	1040
15-16 y	14127
16-17 y	8007
17-18 y	7624
18-19 y	4047
19-20 y	168

Tab. 1: Distribution of the dataset fingerprints. In the notation, *m* stands for month and *y* for year.

Paper based	Live Scanners	Total 208832
29867	148976	178843

Tab. 2: Distribution of the dataset in relation to the type of image. From a total of 178843, roughly a 17% are paper-based images. The rest are obtained through two different 500 *dpi* scanners. See Figure 1 for a sample of these images.

4.2 Question one : with standard hardware and software, starting at what age are fingerprints useful for identification purposes?

As mentioned in the introduction, the main objective of the present work is to analyze the use of child fingerprints for identification purposes. Thus, we need to analyze the quality and performance of fingerprints from very young individuals up to an age for which we already know that the accuracy is acceptable. Thus, we have selected a subset from our dataset, composed by fingerprints acquired between birth and the age of 12. A description of this subset follows next.

4.2.1 Sub Dataset One

For this test, we have selected **45395 fingerprint images pairs**. The selection criteria was to not include in this test pairs of images in which one of them corresponds to an adult (over 12 years old). The other important consideration to select the information contained in this subset was to include only fingerprints acquired using live-scans (no paper-based images are included). This was done in order to remove the possible impact of paper-based fingerprints in the analysis. The fingerprints were acquired using two different commercial scanners with similar characteristics

1. Because of Data Privacy Regulations, the dataset is not publicly available. All the tests and experiments described in this article were done at DNIC facilities, in compliance with Uruguayan law.

Gallery Dataset		Query Dataset														
Age	Total	0-1 m	1-2 m	2-3 m	3-4 m	4-5 m	5-6 m	6-12 m	1-2 y	2-3 y	3-4 y	4-5 y	5-6 y	6-7 y	7-8 y	8-10 y
0-1 m	13421	540	622	631	692	586	698	3239	731	0	14					
1-2 m	5435	0	242	250	198	382	302	1281	290	0	0					
2-3 m	931	0	0	64	64	22	54	272	109	0	0	0	0	0	0	0
3-4 m	734	0	0	0	70	36	40	288	64	0	0	0	0	0	0	0
5-6 m	416	0	0	0	0	0	52	72	100		0	0	0			
6-12 m	1300	0	0	0	0	0	0	328	640							
1-2 y	2068	0	0	0	0	0	0	0	1006	744	40	0	240			
2-3 y	2048	0	0	0	0	0	0	0	0	1124	762	20	836	108		
5-6 y	54560	0	0	0	0	0	0	0	0	0	0	0	22904	15224	5150	1532

Tab. 3: Distribution of samples for age range.

(a) 10d (b) 35d (c) 1y6m (d) 5y (e) 9y (f) Adult (g) 5y (h) Adult

Fig. 2: Sample of images from dataset 1 (a to f) using two different types of sensor and dataset 2 (g and h) using ink templates for 5 years and digital sensor for adult. (d=days, m=months, y=years)

(both uni-dactilar 500 *dpi*, compliant with FBI standards [8]), during the normal identity verification process, which is done in all of the 35 offices that the Agency has around the country.

4.3 Question two: with standard hardware and software, what is the accuracy of fingerprint comparison between fingerprints of 5-year old minors recaptured 10 years later?

The second question we want to answer in this work is whether the accuracy of fingerprint comparison between fingerprints from minors and adults is *good enough* for identification purposes. This problem is strictly related to the *ageing effect* since the time lapse between acquisitions is important. In our particular case, this time lapse is always 10 years or more.

4.3.1 Sub Dataset Two

For this set of experiments, we have selected a dataset of 10000 individuals. Each individual has two fingerprint sets: one set obtained exactly at the age of 5, and a second set of fingerprints acquired approximately at the age of 15. Because the renewal process implemented at DNIC requires only one subset of the ten fingerprints, most of the pairs of this dataset were built using the thumb and the index of both hands. Thus, approximately 30000 genuine pairs were available (29502). One final remark: because we are comparing fingerprints of people that are at least 15 years old, and because the digital acquisition of fingerprints was introduced in 2011, all child fingerprints on this dataset are paper-based. Thus, in this test, we are normally comparing paper-based fingerprints with live-scan fingerprints. Table 4 shows the distribution of ages at acquisition time in the dataset. As we can see, all child images were acquired at the age of 5 (60 months) whereas the adult ones are distributed between 15 and 18 years old (there is always at least 10 years between any pair of corresponding fingerprints).

Age	Fingerprints
5	29867
14	16
15	1040
16	14127
17	8007
18	7624
19	4047
20	168

Tab. 4: Distribution of the aquisition time in Dataset 2 and distribution of the query dataset, gallery is composed of 29867 images, all of them acquired at 5 years old.

5 Framework

In this section, we introduce the framework used to perform the different experiments. In particular, we present the pre-processing steps applied to the fingerprint images. As we will see in the Experiments, this pre-processing is important: without it, child fingerprints cannot be used by commercial software.

5.1 Pre-processing

One of the reasons why children identification is challenging is that most of the commercial systems are implemented and configured to work with adult fingerprints. This was already reported in [7] using NFIQ 2.0 as a quantitative measure of the quality of the fingerprints. A similar result was obtained in this work, as we will show in the Experiments section. In order to use existing commercial systems, we need to pre-process the child

fingerprints in such a way that the resulting image is well suited for these systems. This pre-processing process consists of two steps: an interpolation (resizing child fingerprints to an adult size) and segmentation (reducing errors on minutiae extraction). Both steps are explained in the following sections.
Because we are interested in the practical use of child fingerprints for identification purposes, at the end of this section we included a brief description of some fusion techniquesthat are later explored in the experimental section.

5.1.1 Scale factor

As presented in the introduction, there are a number of works that address the issues related to how to resize child fingerprint images. In [2], [7], a fixed scale factor of 1.8 was used, for fingerprints acquired at 500 *dpi*. In this work, we try to obtain a scale factor that depends on age, and apply this obtained scale factor to resize the image to adult size. It is important to note that even when we compare two child fingerprints, we rescale both of them to an adult size, enabling the use of existing commercial software. To determine the scale factor for each age, we first analyze the distance between ridges. Due to the fact that fingerprint ridge directions are not uniform, it is not possible to use profiles to measure the distance. Therefore, it was necessary to apply a more sophisticated method. We implemented an algorithm that measures the distance based mainly in frequency domain analysis [9]. For a more detailed description of the implementation, see Appendix A. For each one of the ages, the median of the distances between ridges was selected, which was later compared with the distance between adult ridges on a 500 *dpi* image (9 pixels). The relation is given by Equation 1:

$$f_{oi} = \frac{\text{distance between ridges on adults}}{\text{distance between ridges on age group}} \tag{1}$$

Figure 3 shows the median value of the distances between ridges and the obtained scale factor, grouped by age. Table 5 summarizes these results. As expected, median value augments as age increases. Table 5 also includes the final scale factors for each age, which are the ones used to interpolate fingerprints in all the experiments done in this work. As expected, with the exception of the newborn range, we can see an increment in the distance between ridges as the age increases In the case of newborns, it was clear that the automatic determination of the distance between ridges hadfailed. This is basically due to the poor resolution obtained with 500 *dpi* scanner for such small fingers, that makes itvirtually impossible to detect where are the ridges in the image (see Figure 4). We could also observe that the maximum scale factor is 1.65, which corresponds to the range from 2 to 3 months of age. We have decided to discard the scale factors from newborn and 1 month oldranges and use instead the one for 2 to 3 month olds (even in the understanding that it should be a little greater).

5.1.2 Interpolation methods

Once we have an estimation for the scale factor to apply to each image, we need to define an interpolation method to do so. After several experiments with different interpolation methods, we have decided to implement a simple bi-cubic interpolation, where the same scale factor is applied in both directions (rows and columns). Although there are a number of interpolation methods much more adjusted to the way in which a finger grows (see for instance [10]), we try to keep this step very simple since the obtained results were good enough for our purposes. Clearly, the use of amore

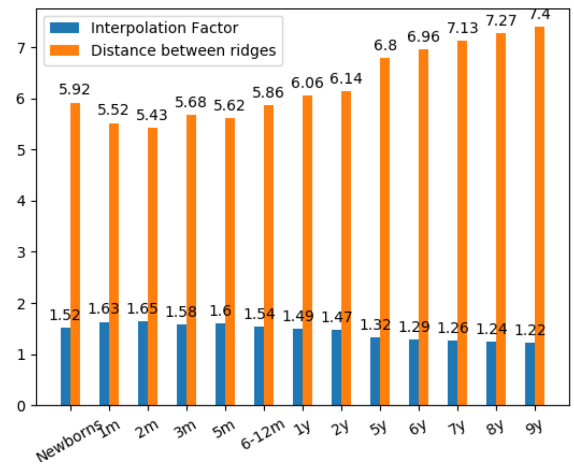


Fig. 3: Distance between ridges and computed scale factor

Fig. 4: Newborn image (less than 30 days). Note how the quality of the image makes it impossible to accurately measure the distances between ridges.

Age Group	Scale Factor	Distance between ridges	Resampled distance between ridges
Newborns	1.52	5,92	8.99
1 m	1.63	5,52	8.99
2 m	1.65	5,43	8.96
3 m	1.58	5,68	8.97
5 m	1.60	5,62	8.99
6-12 m	1.54	5,86	9.02
1 y	1,49	6,06	9.03
2 y	1.47	6,14	9.03
5 y	1.32	6.80	8.98
6 y	1.29	6,96	8.98
7 y	1.26	7,13	8.98
8 y	1.24	7,27	9.01
9 y	1.22	7,40	9.03

Tab. 5: Scale factor and distance between ridges for each set.

sophisticated interpolation method can not but improve these results. Figure 5 shows some examples of the interpolation method applied to an image of a 3 month old child. A more detailed analysis of the different interpolation methods was included in Appendix B.

(a) Before interpolation (b) After interpolation

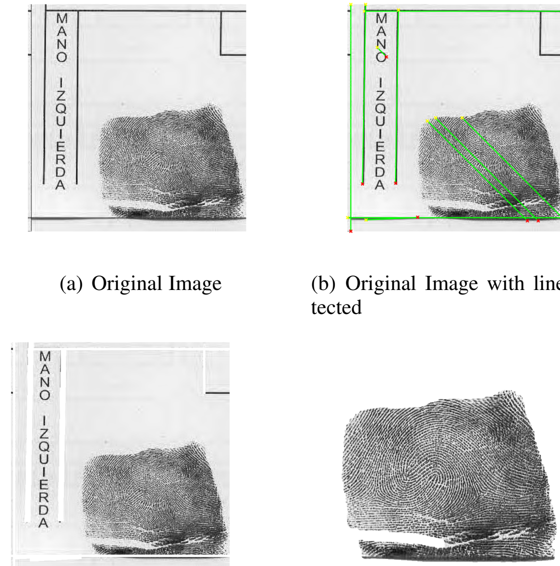
Fig. 5: Example of the interpolation method applied to an image from a 3 month old child (applied factor was 1.58)

5.2 Segmentation

Depending on the source of the input image, there may be the need to segment it prior to the matching process. This problem is more evident in the case of paper-based images, where lines, text and other elements are present (see Figure 1). Without a proper segmentation, some algorithms may find minutiae outside the region of the fingerprint, resulting in a decrease on the accuracy. In order to avoid this problem, fingerprints are segmented based on morphological processing [11]. An example of a fingerprint segmentation can be seen in Figure 6. First, line segments are found using theHough transform algorithm [12]. If those lines contain a strong dark profile along the line direction then the line is erased, otherwise it could be construed as belonging to the fingerprint, as can be seen with the green lines on Figure 6(b). Once the image is cleaned as shown in Figure 6(c), morphological processing is done, strongly based in the ”Fahmy and Thabet” algorithm [11], where opening, closure and an adaptive filter are processed to remove the background (noise) from the foreground (fingerprint). The final result is shown in Figure 6(d)

5.3 Fusion

Biometrics, as other pattern recognition systems, can benefit greatly from fusion strategies [13]. This is the case when working with fingerprints, since multiple samples can be obtained from one person, capturing the impressions of several fingers. The use of more than one fingerprint generally improves the result with respect to the use of only one. This process is used extensively as a way to obtain better accuracy, particularly in national ID and passport issuance systems (which are usually based on 4, 6 or even more fingerprints). In [14], the basis and formalization of biometric fusion strategies were established. The schemes presented in the article are widely used ([15], [16], [17], [18], [19]) for their simplicity, ease of implementation, and because they do not require training. While the use of trained models [17], [20], can provide better performance than the use of simple rules such as those described [14], they require the selection of correct parameters. In this work, fusion is used in the matching score level. The scores combination is done through the addition like in [7].



(a) Original Image (b) Original Image with lines detected

(c) Original Image with lines erased (d) Segmented Image

Fig. 6: Sample of segmentation

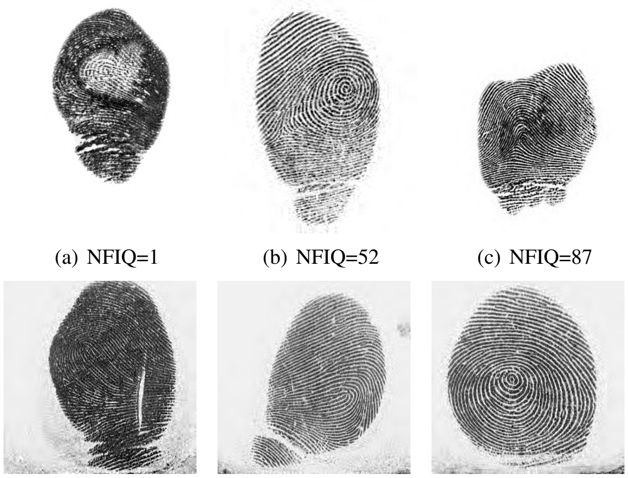
6 EXPERIMENTS AND RESULTS

In this section, we present the different experiments performed during this work. The first experiment analyzes the relation between the size of the image and the quality. As expected, the quality is strictly related to the image size. This fact is confirmed after pre-processing, since after resizing the images, the quality increases.

6.1 Relation between quality and image size

The performance of biometrics systems depends to a great extent on the quality of the data. Therefore, quality indicators can be used as a way to compare the effectiveness of different preprocessing methods. In this work we used NFIQ 2.0 [21], which assigns a number from 0 to 100, directly related to the performance prediction of the matcher evaluating a single fingerprint. As shown in our preliminary work [4], most commercial and non-commercial matcher algorithms were implemented to deal with adult fingerprints. Because the NFIQ 2.0 algorithm is strongly related to the performance of the available matching algorithms, it suffers from the same problems: NFIQ 2.0 gives very bad quality values for images acquired from children aged 0 to 6. We illustrate this problem with some fingerprint samples in Figure 7.

In [4] we show that a very simple scale strategy (bi-cubic interpolation) improves the results of the NFIQ 2.0. Table 6 summarizes NFIQ 2.0 quality before and after pre-processing, ordered by age. It is clear from these results that quality increases when pre-processing is applied, confirming the hypothesis that NFIQ 2.0 is affected by the image size. The table also shows that for ages 5 to 6,the improvement goes from a mean quality value of 36.03 to a mean quality value of 48.56, which is in the range of the quality value for adults (NIST MFCP 2: 45.98). But even for ages 2 to 3 the quality obtained after pre-processing is comparable to the one obtained for adults.



(a) NFIQ=1 (b) NFIQ=52 (c) NFIQ=87

(d) NFIQ=1 (e) NFIQ=50 (f) NFIQ=78

Fig. 7: Examples of quality with NFIQ 2.0 for different sensors

Age Group	Numbers of fingerprints	Initial Quality (mean)	Quality after pre-processing (mean)	Variance
Newborns	2264	1,68	2,62	4,37
1-2 m	2176	2,25	6,98	9,19
2-3 m	733	2,66	9,83	11,55
3-4 m	288	3,46	8,17	11,95
5-6 m	161	3,59	10,37	9,97
6-12 m	482	6,12	14,16	15,07
1-2 y	712	14,50	30,23	20,53
2-3 y	784	23,55	42,83	22,96
5-6 y	2963	36,03	48,56	25,48
Adults (NIST MFCP 2)	1086	45,98	-	-

Tab. 6: NFIQ 2.0 data quality before and after pre-processing, grouped by age. Note how the quality increases after pre-processing, reaching for 2 to 6 year olds, values similar to the ones obtained for adult fingerprints.

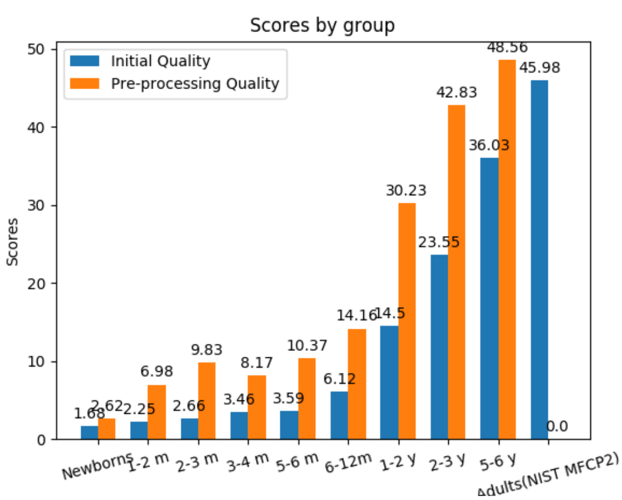


Fig. 8: Initial Quality and resulting Quality after applying the resize technique. Quality is measured by NFIQ 2.0

Because NFIQ 2.0 is strictly related to the matching process, and the matching process itself is based on the minutiae, it is interesting to analyze how minutiae detection is affected by age. Table 7 shows the number of minutiae obtained before and after pre-processing, grouped by age. Although it is true that there might be a number of false positives for lower age ranges, the amount of fingerprints with minutiae increases from 6% to 84% in the worst case. Pre-processing is clearly necessary for data obtained from children of up to 2 years of age , where the table shows more improvements, and even though the number of fingerprint with minutiae is the same for the age range of 5-6 years, we will see in following sections that pre-processing is also necessary in those cases.

Age Group	Numbers of fingerprints	Numbers of fingerprints with minutiae	Numbers of fingerprints with minutiae after pre-processing
Newborns	100	6	84
1-2 m	100	7	88
2-3 m	100	12	93
3-4 m	100	13	89
5-6 m	98	36	95
6-12 m	100	47	100
1-2 y	100	85	99
2-3 y	100	91	99
5-6 y	100	100	100

Tab. 7: Amount of minutiae by age ranges before and after pre-processing.

6.2 Question one: with standard hardware and software, from which age are fingerprints useful for identification purposes ?

In order to answer this question, one of the first experiments to perform is the analysis of how fingerprint identification is affected by the age of the individual. First, we need to introduce the metrics that we will use. Given a pair of fingerprint images q_i, q_j, let d be the distance function and let id be the function that returns the correct identity for a given sample q_i. Given a threshold δ, we define the following metrics:

- **True acceptance rate** (TAR): which is the percentage of times that the system correctly verifies a true claim of identity.
$$TAR(\delta) = 1 - FRR(\delta) \tag{2}$$
where False Rejection Rate (FRR) is defined as:
$$FRR(\delta) = \frac{\#d(q_i, q_j) < \delta \ \ t.q \ \ id(q_i) = id(q_j)}{N} \tag{3}$$
- **False Acceptance Rate** (FAR): which is the probability that the system incorrectly matches the input pattern to a non-matching template in the database.
$$FAR(\delta) = \frac{\#d(q_i, q_j) > \delta \ \ t.q \ \ id(q_i) \neq id(q_j)}{N(N-1)} \tag{4}$$
- **Receiver Operating Characteristics** (ROC): curve that is plotted as TAR vs FAR at different thresholds (from 0 to 1) to indicate the verification performance.

In order to compute the FAR, we need to have a set of impostors. For this experiment, we have created this set by comparing each of the IDs in the Query dataset with all the IDs in the Gallery dataset, leaving out fingerprints of the same id.

Finally, note that FAR/FRR definitions given above slightly differ from the definitions given in ISO/IEC 19795, where a distinction is made between errors at the algorithm level and errors at the system level. In ISO/IEC 19795, the errors at the algorithm level are defined as False Match Rate (FMR) and False Non-Match Rate (FNMR). Because most of the works we referenced use the FAR/FRR definitions given above, we've decided to maintain them. In any case, there is no ambiguity since the context in which we do all the analysis is at the algorithm level.

6.2.1 Analysis of the age effect

In this first experiment, we compare the results obtained using the corresponding scale factor obtained from Table 5 for different databases grouped by age. Figure 9 and Table 8 present the results. We also include the results obtained from an adult database (NIST MFCP2 database [22]) for comparison purposes.

Age Group	TAR (%)	TAR (%) with preprocessing
Newborns	NA	1,25
1-2 m	NA	7,57
2-3 m	NA	15,61
3-4 m	NA	10,53
5-6 m	NA	20,00
6-12 m	2,53	34,88
1-2 y	18,12	61,88
2-3 y	27,24	78,37
5-6 y (2000)	74,41	92,64
NIST MFCP 2	98,39	98,39

Tab. 8: Performance given by TAR for a fixed FAR in 0.1%

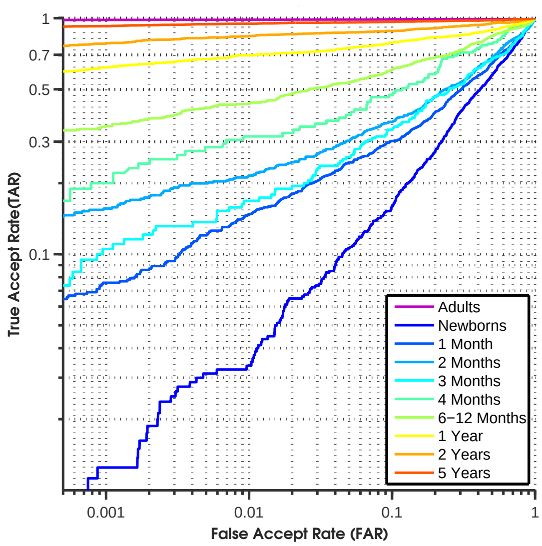


Fig. 9: Performance of every set interpolating by table I factors

We can see that the TAR obtained for the 5-6 age range ($92,64\%$ for a FAR of 0.1%) is comparable to the one obtained for adults ($98,39\%$). Even the 1-2 and 2-3 age ranges present good results ($61,88\%$ and $78,37\%$ respectively). We recall that in all these experiments, the comparison was done considering only one fingerprint per identity.

If we compare now the results obtained for one and five year olds, with the performance obtained on the adult database (Table 8 and Figure 10), we can see that interpolation is mandatory to obtain good results. What is more, applying the correct scale factor improves the results in the case of five year olds,as we can see when we compare the results obtained using the scale factor from Table 5 and the one obtained with a scale factor of 1.8. In the case of one year olds, we obtained almost the same performance for both scale factors. Since selected minutiae extractor works with a default image size, by using the proposed scale factor we make sure that we are looking for minutiae throughout the whole fingerprint.

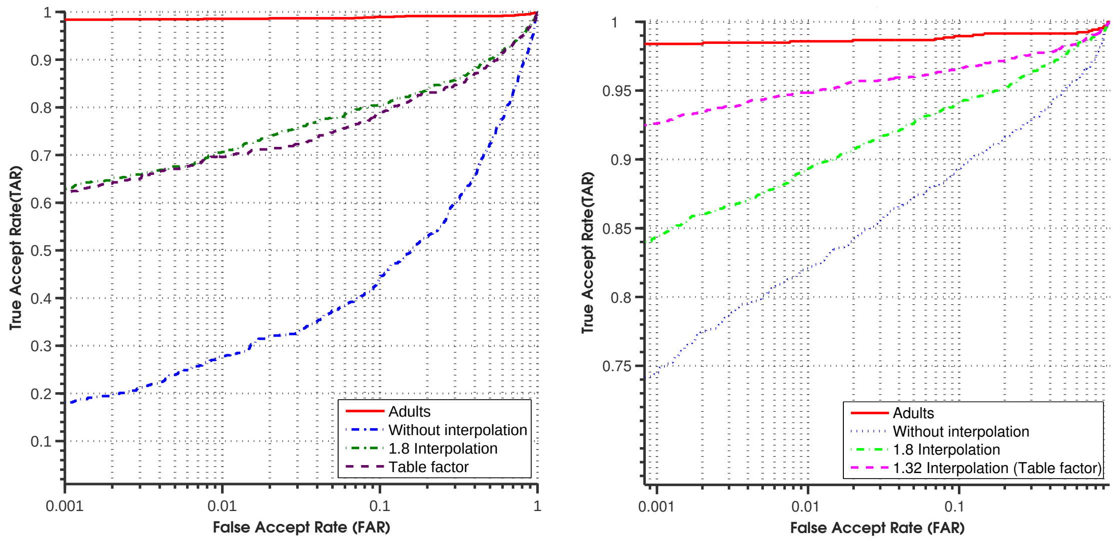
6.2.2 Analysis of fusion

In order to compare our results with the one obtained in [7], we performed another experiment, where we considered two fingerprints for each individual (right thumb and right index). In the dataset corresponding to five year olds, where we have 599 individuals, we obtained a TAR of 98.33% at a fixed FAR in 0.1%. From a total of 111 subjects in one year database, we obtained a TAR of 79.28% at a fixed FAR in 0.1%. In [7], authors reported a TAR of 100% for a fixed FAR in 0.1% for 1 to 5 year old children.When we replicated the experiment with our dataset (applying 1.8 factor), we obtained a TAR 90.65% for five year olds and a TAR of 81.42% for one year olds,in both cases with a FAR of 0.1 %. We believe that the main differences with the result reported in [7] is obviously the source of the dataset. In our case, the data was obtained directly from the on-production environment, without any participation in the way fingerprints were acquired. We consider that the results obtained from the fusion experiment (which is in fact the usual scenario on identification, where in general we have more than one fingerprint per individual) are very illustrative and suggest that fingerprints can be used to identify children as young as one year olds. This claim is supported with the data used in this work, obtained directly from an on-production system.

6.3 Question Two: With standard hardware and software, what is the accuracy of fingerprint comparison between fingerprints of 5-year old minors recaptured 10 years later?

In order to answer this question, we have run the following experiment. As usual, the set was divided between genuine and impostor datasets. We used the fingerprints of 5 year olds as the gallery set, and the adult fingerprint as the query dataset (which, additionally, better represents the real situation in Uruguay, where the fingerprints of 5 year olds are the ones stored in the National ID database). In order to obtain a bigger number of genuines, and knowing the small correlation between samples of the same person, we decided to consider each fingerprint pair independently of identity. This way, we had nearly 30000 genuines pairs. For the impostors, we decided to do the analysis using the same amount of pairs by randomly sampling the pairs. As explained before, one of the main objectives of this study is to understand fingerprint image comparison on standard conditions. For this experiment, we have used a different commercial matcher than the one used for the previous experiments. This matcher faces the same lack of robustness for child fingerprints. In fact, when no scale factor was applied to the images, the matcher failed in all cases. This is why we have decided, for this experiment, to apply the scale factor described in Table 5, which, for 5 year olds , is 1.32.

The results are presented in Figure 11 and Table 10. It is clear, from these results, that the comparison for fingerprints between children and adults is comparable to those of adults vs adults: for a FAR of 0.01% (0.0001), we obtain a TAR of 97.5%, and a TAR



(a) Comparison between adults and 1 year old performance

(b) Comparison between adults and 5 year old performance

Fig. 10: A comparison between True Acceptance Rate vs False Acceptance Rate Curves for adults and minors.

	SF=1	SF proposed	SF=1,8	Fusion SF proposed	Fusion SF=1.8
TAR (%) five years	74,41	92,64	84,35	98.33	90.65
TAR (%) one year	18.12	61,88	62.34	79.28	81.42
TAR(%) Adults	98.39	-	-	-	-

Tab. 9: Performance given by TAR for a fixed FAR in 0.1% for scale factor of 1.8 and the proposed, with and without fusion for two fingers, (SF = scale factor)

of 97.9% for a FAR of 0.1% (comparable with the TAR obtained for adults only: 98.39%).

Age Group	FAR (%)	TAR (%)
	0.01	97.5
	0.1	97.9

Tab. 10: Results for the child vs adult comparison. A scale factor of 1.32 was applied to the child fingerprints

7 Conclusions and Future Work

In this work, we presented an analysis on the use of fingerprint images for child identification and verification. We performed all the study with data obtained from a production environment, where fingerprints images were acquired from an ID card and passport issuance system. We are now in a position to answer the two questions that have been guiding this work:

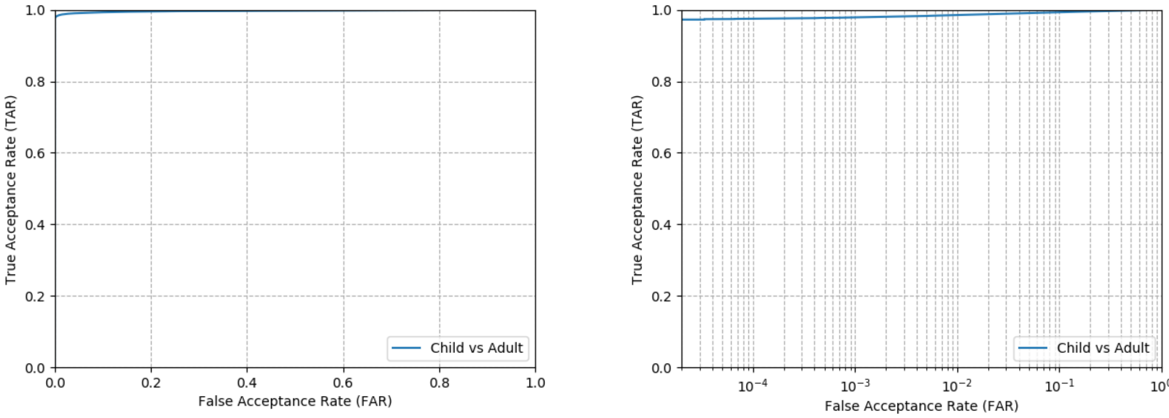
Question one: With standard hardware and software, starting at which age are fingerprints images useful for identification purposes ?

- We have shown that, after applying a growth factor interpolation method to child fingerprint images, quality improves. For five year olds , the quality obtained after pre-processing is better than the one obtained for adult fingerprints (48.56 vs 45.98), and even the quality obtained for children aged two and older are comparable (42.83). We havealso shown that this interpolation is necessary: minor fingerprints in their original size obtain very low quality,as shown in Table 6.
- Using this approach, the accuracy obtained in the matching process for five year olds' fingerprints is already good: a TAR of 92.64% compared with a TAR of 98.39% for adults,in both cases with a FAR of 0.1%. What is more, when we consider two fingerprints for the five year olds case, the result is basically the same to the one obtained when analyzing one adult fingerprint: 98.33% and 98.39% respectively.
- Even in the case of images obtained from one year olds, the TAR obtained (62.3%) for a FAR of 0.1% is still relevant. Indeed, if we consider a fusion technique for two fingerprints, the resulting TAR jumps to 81.42%. Although these results are not comparable to those obtained for adults, the accuracy obtained may be relevant for practical situations. Further research is needed to confirm if, using more fingerprints, an accuracy similar to adults is possible.

Question two: With standard hardware and software, what is the accuracy of fingerprint comparison between fingerprints of 5-year old minors recaptured 10 years later?

- We have shown that the accuracy obtained when comparing fingerprints from 5 year olds with those obtained 10 years later (from 15 year olds or older) is similar to the one obtained when adults fingerprints are compared: for a fixed FAR of 0.1%, the obtained TAR was 97.9%, very similar to the 98.39% obtained for adults.

In future work, we want to focus on the youngest age range: from newborns to one year old. Since one of the biggest limitations in this case is the low quality of the acquired images, we are



(a) ROC Curve

(b) Zoom

Fig. 11: ROC Curves of child vs adult comparison. A scale factor of 1.32 was applied to the child fingerprints

preparing a campaign with high resolution scanners. Preliminary experiments with a 2000 dpi prototype show promising results. In addition, we want to make further research on a more advanced ageing model for fingers, which can further improve the performance of the systems.

Appendix A
Ridge distance

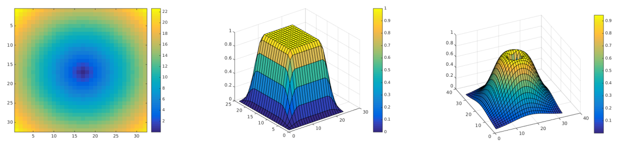
To measure the ridge distance, we split the fingerprint image in small blocks of size $tbloq$. This variable must contain at least 3-4 ridges for a good estimation, so, knowing that the distance for adults is 9 pixels (for a 500 dpi sensor), the parameter $tbloq$ must be higher than 27. On this study, $tbloq = 32$.

The description of the algorithm is as follow:

Algorithm 1 Ridges distance algorithm

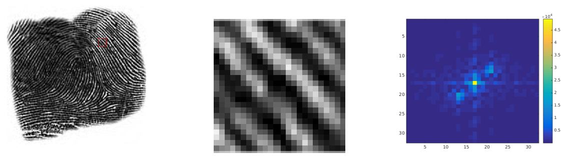
1: **Input** Image $I(x, y)$, $tbloq$
2: $[x, y] \leftarrow meshgrid(-tbloq/2 : tbloq/2 - 1, -tbloq/2 : tbloq/2 - 1)$
3: $r \leftarrow sqrt(x.^2 + y.^2) + eps$
4: $w \leftarrow$ Raised-cosine filter
5: $dRLow = 1./(1 + (r/10).^4)$ (low_pass filter)
6: $dRHigh = 1./(1 + (3./r).^4)$ (high_pass filter)
7: $band\_pass = dRLow. \times dRHigh$
8: $blk_i \leftarrow$ split I in blocks of size $tbloq \times tbloq$
9: **for** i=1 to # blk **do**
10: $\quad mean\_blk \leftarrow sum(blk)/(tbloq \times tbloq)$
11: $\quad blk \leftarrow blk - mean\_blk$
12: $\quad blk \leftarrow blk. \times w$
13: $\quad blkfft \leftarrow fourier(blk)$
14: $\quad blkfft \leftarrow blkfft. \times band\_pass$
15: $\quad energy \leftarrow |blkfft|.^3$
16: $\quad frecuency_i \leftarrow sum(energy. \times r)/sum(energy + \epsilon)$
17: $\quad mat\_ridge\_dist_i \leftarrow tbloq/frecuency_i$
18: **end for**
19: $M \times N \leftarrow size(mat\_ridge\_dist)$
20: $ridge\_dist \leftarrow median(mat\_ridge\_dist(M/3 : 2M/3, N/3 : 2N/3))$
21: **return** $ridge\_dist$

Figure 13 shows how the proposed algorithm processes the image, step by step, to estimate the distance between ridges. The original image can be seen in image 13(a), an example of block in 13(b) and the Fourier Transform of the block in 13(c). Steps 2 to 7 create the filters that are used to process the frequency, those filters are shown in Figure 12. Images from 13(d) to 13(f) show the image processing related to steps 10 to 15 respectively. After these steps, for each block the frequency is extracted from the energy as in step 16, and then converted to distance by step 17. Once all of the blocks are processed, a median function is calculated with the distances for all the blocks that are in the center region of the image. This is done to deprecate the contours of the fingerprints. The algorithm then returns this median value.

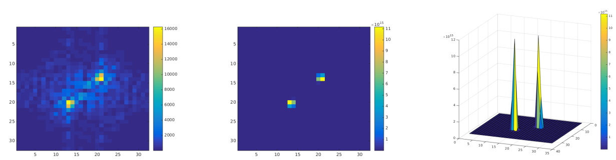


(a) Auxiliary filter r (b) Raised-cosine filter (c) Pass-band filter

Fig. 12: Filters used in steps 3, 4 and 7 on Ridges distance algorithm



(a) (b) (c)



(d) (e) (f)

Fig. 13: Frequency processing, a) Original image, b) Block taken, c) Fourier transform of the block, d) Fourier transform of the previous block after the offset removing, e) Fourier transform of the previous block after Raised-cosine filtering, pass-band filtering and calculation of energy, f) Energy of the block in 3D.

Appendix B
Interpolation methods

We continue our experiments by analyzing different interpolation methods. We compare a classic bi-cubic interpolation with two other interpolation methods: Interpolation with Geometric Contour Stencils [23] and Tensor-Driven Diffusion for Image Interpolation [24]. Figure 14 presents the results obtained on dataset with 720 fingerprints obtained from one year old children. In all cases, we use the interpolation factor described in Table 5. We can see that there is no significant difference between the different methods. In fact, the bi-cubic interpolation obtains better results.

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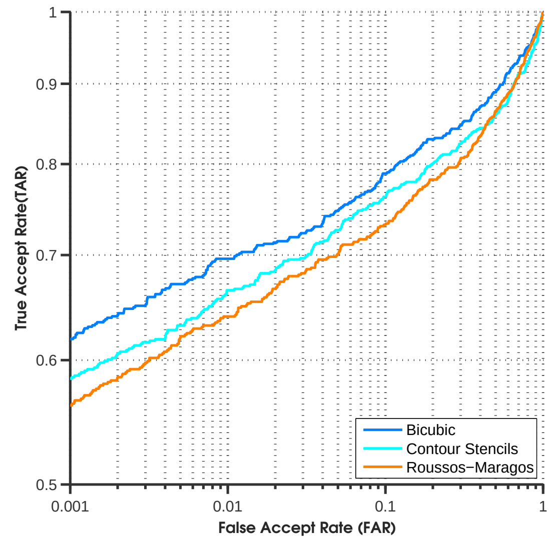

Fig. 14: Different interpolation performances over base with 720 fingerprints obtained from one year olds

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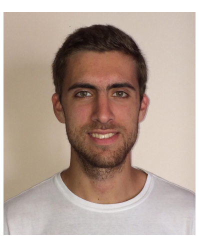

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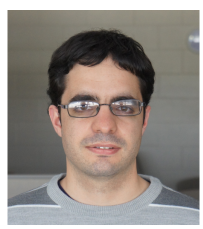

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