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Automatic fingerprint recognition: from children to elderly

Ageing and age effects

Beslay, L.
Galbally, J.
Haraksim, R.

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Contact information
Name: Laurent Beslay
Address: Via. E.Fermi 2749 – Ispra (VA) - Italy
Email: Laurent.beslay@ec.europa.eu
Tel.: +39 0332 78 6556

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Abstract

By courtesy of the Portuguese Government, DG JRC has received a comprehensive set of fingerprint data from individuals aged 0-25 and 65-98. The main purpose of the proposed experiments is to deepen the understanding regarding the physiological development of the fingertip ridge structure over time and its impact on automated fingerprint recognition. The experiments explore three biometric processes in the light of age, ageing and growth effects. These effects are demonstrated and validated. A growth model is also developed and validated. The report concludes with a series of recommendations for enhanced implementation of automated fingerprint recognition system and suggestions for further researches.

1 Introduction

By courtesy of the Portuguese Government, DG JRC has received a comprehensive set of fingerprint data from individuals aged 0-25 and 65-98. This dataset follows an earlier collaboration between DG JRC and the Portuguese Authorities related to a smaller set of fingerprints of children below the age of 12, which was the subject of a first JRC Technical Report [1].

The main purpose for the second cooperation is to conduct further experiments, following the first campaign, in order to deepen the understanding regarding the physiological development of the fingertip ridge structure over time and its impact on automated fingerprint recognition. Time produces variations in the accuracy of fingerprint recognition systems. Such accuracy variations may be explained by different factors such as: change in the quality of the fingerprints (due to time), changes in the morphology of the fingerprints due to growth or usage (degradation, scars, etc.).

Quality of data is not only a privacy and data protection principle enshrined in the EU regulatory framework, it also constitutes a determinant factor of the efficient functioning of large scale EU biometric systems such as EURODAC, VIS, SIS, or national ones such as passport and Identity national registries. It is therefore of utmost importance to identify and quantify accurately the challenges faced for obtaining high quality of fingerprint data in order to propose innovative solutions and procedural measures for the improvement of this quality level. Higher quality for those systems means also fewer false rejection cases leading to a higher acceptance and trust levels for those systems.

1.1 Purpose of the experiments

The experiments will explore the three following biometric processes in the light of age, ageing and growth effects:

1. **Quality metrics algorithm and age effect:** assess the variation of quality for three different age groups (children, adults, and elderly), which in this study will be referred to as the **"age effect"**. This evaluation will permit to explore the possibility to develop more suitable metrics, in order to address fingerprint age issues and to achieve better estimation of the expected recognition performance.
2. **Matching performance and age and ageing effects:** assess the variation of performance of automated fingerprint recognition software for three different age groups (children, adults, and elderly), evaluating the age effect. The study will also explore the impact of the "**ageing effect**" on the performance of the matching algorithms, which is defined as the variation in the matching performance when the time lapse between enrolment and query images increases.
3. **Fingerprint pattern growth model:** identification and validation of the appropriate growth model of the fingertip ridge structure and the extent to which this model can predict the position of fingerprint features over time.

Addressing these challenges and mitigating their effects is of primary importance for the EU Member States and the European Commission, as it will contribute to reduce possible errors from large scale biometric systems and enhance the end-user experience.

1.2 Main findings of the first 2013 JRC study

Benefiting from a first fruitful cooperation with the Portuguese authority, DG JRC conducted a series of experiments on a dataset comprising 1612 individuals from 0 to 12 years. The study concluded that ***fingerprint recognition of children aged between 6 and 12 years is achievable with a satisfactory level of accuracy***. This main conclusion relied on a series of findings, such as:

- Quality of children fingerprints is the key to obtain good accuracy.

- Matching algorithms can be further improved through the development of a reliable growth model.
- The need for a statistically relevant (larger) test dataset with long-term data in order to support more in-depth studies.

The 2013 JRC study underlined also its limits and the possibility for future research. The study was conducted on children fingerprints only and it was highlighted, that the adult data should be made available for calibration and reference, together with other age groups. These preliminary findings confirmed the need for the development of isotropic growth model, which should be done over a longer time frame and supported by a large quantity of data.

1.3 Scientific studies since 2013 on effects of Age and Ageing on Fingerprints

Following the initial 2013 JRC study and as a result of growing attention paid by the scientific community in recent years to the study of age effects on different biometric modalities a series of scientific experiments and research documents were published. In 2013, a book dedicated to this issue was published with the contribution of many researchers that addressed different aspects of this area in very diverse biometric traits, including fingerprints [2]. The book includes studies on topics such as the age effect, ageing effect, template update strategies or growth models and age prediction.

With the unavoidable risk of not being completely exhaustive, some of those scientific publications are briefly introduced below.

1.3.1 Specific references on age and fingerprints

Researchers at the University of Michigan studied the possibility of fingerprinting young children (0-4 years) in order to improve the efficiency of the immunisation program in India [3]. Involving two groups of 20 and 70 subjects, the study reached the following conclusions regarding (young) childrens fingerprints:

- Low quality of fingerprints is due to non-cooperative subjects, oily and wet finger skin and last but not least, the very small size of the fingers which are triggering issues with fingerprint sensors originally designed for adults.
- The fusion of several fingers and/or of multiple templates constitute potentially good matching strategies and increase the matching performance of commercial readers.

In a following study in 2017 [4], the same research team from Michigan State University, continued the research on fingerprint recognition of very young children. In this case, a database of 309 subjects aged between 0 and 5 years was produced in four sessions separated over the course of one year. The three key questions addressed by the study were: (i) do fingerprints of children possess the salient features necessary to attribute a unique identity to each child?, (ii) if so, at what age is it possible to capture a child's fingerprints with sufficient fidelity for recognition?, and (iii) can a child's fingerprints be used to reliably recognize the child as (s)he ages? The conclusions of the research were that:

- 500 ppi fingerprints suffice for recognizing children at least 12 months of age.
- 1,270 ppi fingerprints are required to recognize children below 12 months of age.
- For very young children the age at enrolment has a larger effect on genuine scores than the time lapse between enrolment and query images (considering a time lapse of 6-12 months).
- The genuine similarity scores do not significantly decrease in a 6-12 months lapse.

1.3.2 Specific references on ageing and fingerprints

A small study on fingerprint ageing was published in two successive articles in 2017 [5], [6]. The research was conducted on the common fingerprint data contained in the databases CASIA 2009 and CASIA 2013. This quite limited set of fingerprints is composed of 10 samples (5 acquired in 2009 and 5 in 2013) of 196 different fingers. The main conclusions of the research are:

- Ageing affects similarly minutiae-based and non-minutiae-based fingerprint recognition systems;
- Quality does not seem to explain by itself the ageing effect, but other factors should also be taken into account such as growth.

In 2015, researchers from Michigan State University published an article that focuses on the analysis of the persistence of fingerprints over time, i.e., the ageing effect [7]. This is, to date, the largest and most comprehensive study in terms of the dataset used. The database was acquired under real operational conditions (law-enforcement context) and contains an average of 8 impressions of the right index of 15,597 subjects over an average time span of 9 years. The main findings of the study are:

- Genuine matching scores tend to decrease as the time interval between two compared fingerprints increases.
- Impostor matching scores are not affected by the time interval between the compared fingerprints.
- In spite of the decrease in the genuine matching scores, the accuracy of the tested systems is fairly stable independently of the time lapse between the compared fingerprints.
- Genuine matching scores continuously decrease with age, for an age range between 0 and 80 years old.
- Quality continuously decreases with age, for an age range between 0 and 80 years old.

2 Dataset

The dataset provided to DG JRC has been acquired for the purpose of issuing biometric passports for which the fingerprints of the two index fingers are registered. If one or more of these fingers are missing other fingers could be used instead.

For the majority of the enrolled persons, fingerprints have been acquired at least twice in time, in some cases even more often. The time difference is quantified by the metadata, which includes the date of birth of the person and the date of the fingerprint acquisition. The metadata does not contain any names, addresses etc. nor an indication regarding the location of the enrolment, nor which fingerprints have been acquired at the same collection place or the gender of the data subject.

Metadata information in the database is integrated into the image filenames. The format is as follows:

<ID-Nr.>_<date of birth (yyyymmdd)>_<date of acquisition (yyyymmdd)>_<finger ID>.WSQ

- ID-Nr. is an anonymized 7-digit number assigned to the records when they were extracted from the Portuguese national passport database. ID-Nr identifies a subject.
- Finger ID identifies which of the 8 fingers or 2 thumbs the image corresponds to. In most cases it takes the value 2 (right hand index) or 7 (left hand index), except for those cases mentioned before (i.e., missing right or left indexes). This way, ID-Nr, together with Finger ID, uniquely identifies one finger of one person.
- WSQ corresponds to the format of the fingerprint image, which is produced by the Wavelet Scalar Quantization algorithm developed by the FBI (a compression algorithm used for gray-scale fingerprint images).

Example: 4395328_19700331_20110806_2.wsq

The person, born on 31.03.1970 has been assigned the ID number 4395328. The fingerprint of the right index finger (2) was acquired on 6.8.2011.

The metadata included in the fingerprint filenames needs to be processed in order to compute the age of the users in the first acquisition (in months) and, should multiple impressions of the same finger exist, the time difference of the successive acquisitions (in months). This information will be used in the experiments described below. The analysis of the metadata allows for individual assessment of the statistical significance of all parts of the data, e.g. age groups.

The passport fingerprints are subject to enrolment in compliance with European and international standards[1] and are collected in controlled conditions. Apart from the cleaning procedure of the dataset described below, the fingerprint records were not subject to translation, rotation, removal of ghost fingerprints or any other pre-processing, since the objective was to keep the matching process as close as possible to the one the individuals undergo in the border control scenario.

2.1 Original dataset

The original dataset received contained the following number of fingerprints:

- Number of fingerprints of persons aged 0-17 years (children): 264,154
- Number of fingerprints of persons aged 18-25 years (adults): 116,410
- Number of fingerprints of persons aged 65-98 (elderly):56,640

[1] Commission Implementing Decision C(2013) 6181 of 30 September 2013 amending Commission Decision C(2006) 2909 final laying down the technical specifications on the standards for security features and biometrics in passports and travel documents issued by Member States and Commission Decision C(2008) 8657 laying down a certificate policy as required in the technical specifications on the standards for security features and biometrics in passports and travel documents issued by Member States and updating the normative reference documents.

- Total number of fingerprints received: **437,204 (from 132,049 individuals).**

The tables below detail the number of samples per finger for each of the three age groups (children, adults and elderly).

Individuals 0-17 (Children):

Number of fingerprint impressions per finger	***Fingers***	***Total Fingerprints***
1	40684	40684
2	106648	213296
3	3156	9468
4	142	568
5	18	90
6	8	48
7	0	0
TOTAL	150656	264154

Individuals 18-25 (Adults):

Number of fingerprint impressions per finger	***Fingers***	***Total Fingerprints***
1	37416	37416
2	37306	74612
3	1198	3594
4	156	624
5	20	100
6	6	36
7	4	28
TOTAL	76106	116410

Individuals 65-98 (Elderly):

Number of fingerprint impressions per finger	*Fingers*	*Total fingerprints*
1	21888	21888
2	16994	33988
3	208	624
4	20	80
5	4	20
6	4	24
7	0	0
8	2	16
TOTAL	39120	56640

A more detailed description is available in Annex 1.

2.2 Cleaning, Ground truth and Correctness of the data provided

The building process of a very large dataset involving human intervention always leads to mistakes in the tagging of the samples that entail errors in the ground truth (e.g., duplicated samples, fingerprints assigned to the wrong finger, etc).

In order to conduct the foreseen scientific experiments on a dataset, which would be as close as possible to its ground truth equivalent, a number of preliminary detection and cleaning processes were applied in order to address the great majority of the mistakes. The mistakes considered were:

1. Detection of swapped fingers (right/left indexes).
2. Wrong resolution encoded in the metadata.
3. Detection of duplicated samples.
4. Detection of absence of a fingerprint pattern in the image.

2.2.1 Swapping of fingers

It has been noted in the course of previous experiments, that due to acquisition errors, a percentage of fingerprints which should have been collected in principle from the same finger (e.g. Finger 2 of an individual enrolled at the time T0 should correspond to the same Finger 2 of the same individual enrolled at the time T1), actually belonged to different fingers (e.g. Finger 2 of an individual enrolled at the time T0 was actually labelled as Finger 7 of the same individual enrolled at the time T1). Consequently, an odd behaviour of the matching algorithms was detected when analysing the genuine quality scores.

In theory, high quality pairs of fingerprints (a high quality was considered for a pair of fingerprints where the average NFIQ2 > 60 and the individual fingerprint NFIQ2 values are > 60) should produce a high matching score (MS > 60 in case of VeriFinger). However, for around 4.8% of the cases where NFIQ2>60 it was found that MS<15. It was found that this theoretical genuine pairs of fingers (the same finger sample enrolled at two different times) were in fact "swapped" or "mislabelled" fingers, which eventually produce matching scores equal to the scores of impostors.

In order to address the most probably wrong assignment of the labels of fingers between left and right hands, the following procedural steps to detect acquisition errors and to confirm the swapping of assigned labels have been applied:

1. Match assumed fingerprint-mates against each other (in other words, genuine matching scores) using the Neurotechnology VeriFinger matching algorithm. For more than 2 FPs per finger, use the FP with highest NFIQ2.0 quality value as the reference sample and check the scores against this value.
2. For the genuine fingerprint comparisons with the matching score >15, consider ground truth approved.
3. For all non-matched samples, swap left and right fingers and repeat step 1. If the score is higher than the one computed in step 1, exchange the concerned fingerprints and consider ground truth established.
4. Use Fingerprint Alignment Software developed by the JRC to visually decide on ground truth regarding the "same" or "different" fingers for all the remaining non-matches (screenshot of the alignment interface is presented below in Figure 1).

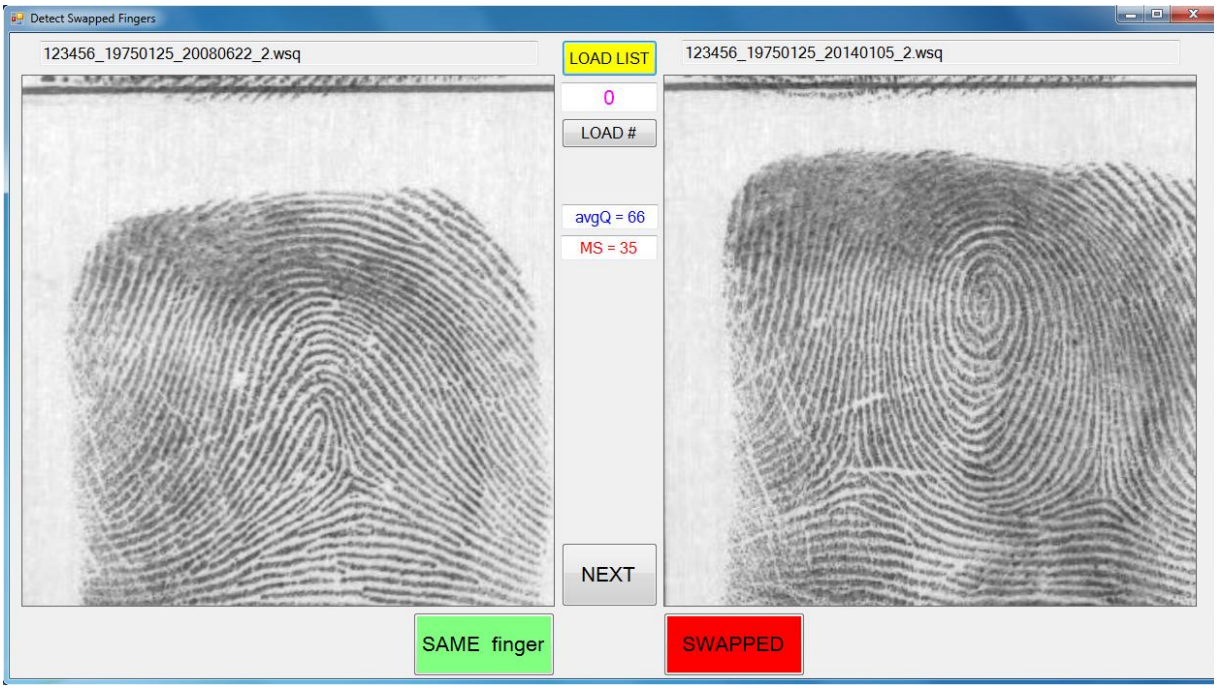

Figure 1 Fingerprint alignment software (swapped fingers example)

5. Earmark and exclude all undecidable remaining cases from the experiments.

The fourth step could be very time consuming if the three first steps result in too many undecided cases. Potential adjustment of the chosen threshold could be envisaged.

The expected result of this step is the correct assignment of the ground truth of the data for the planned objectives of the study presented in the introduction. Therefore it was decided to address this issue programmatically using machine learning algorithms.

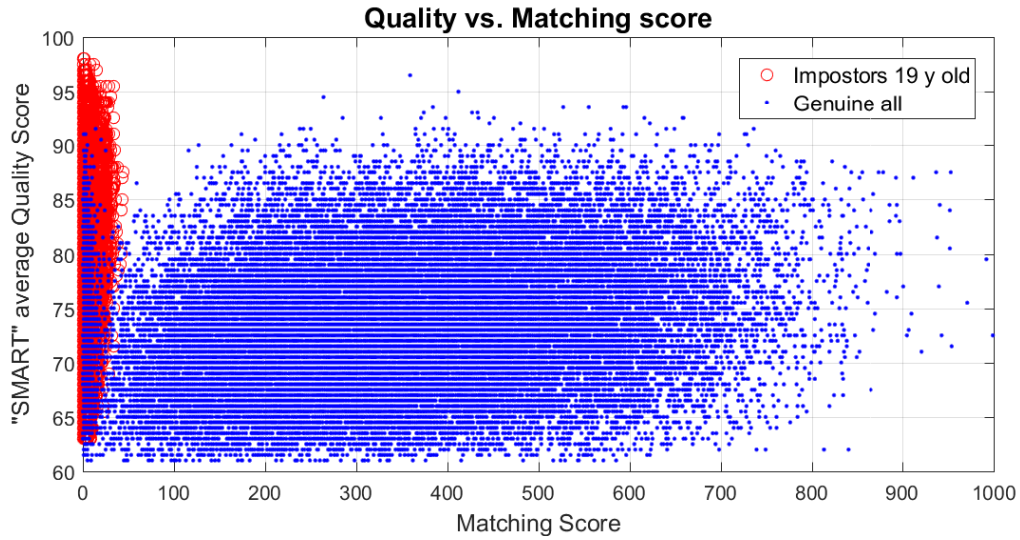

Figure 2 Genuine matching scores distribution vs pairs of fingerprints with NFIQ2 > 60

The extent of the swapped fingers problem is illustrated in Figure 2 above, where red circles represent the reference impostor score distribution for a control population of 19-year olds and blue dots represent the genuine score distribution obtained from step 1 of the cleaning procedure. This impostor reference dataset was chosen based on the sufficient quantity of the impostor scores satisfying the NFIQ2 > 60 quality condition (more than 300,000 impostor Matching Scores).

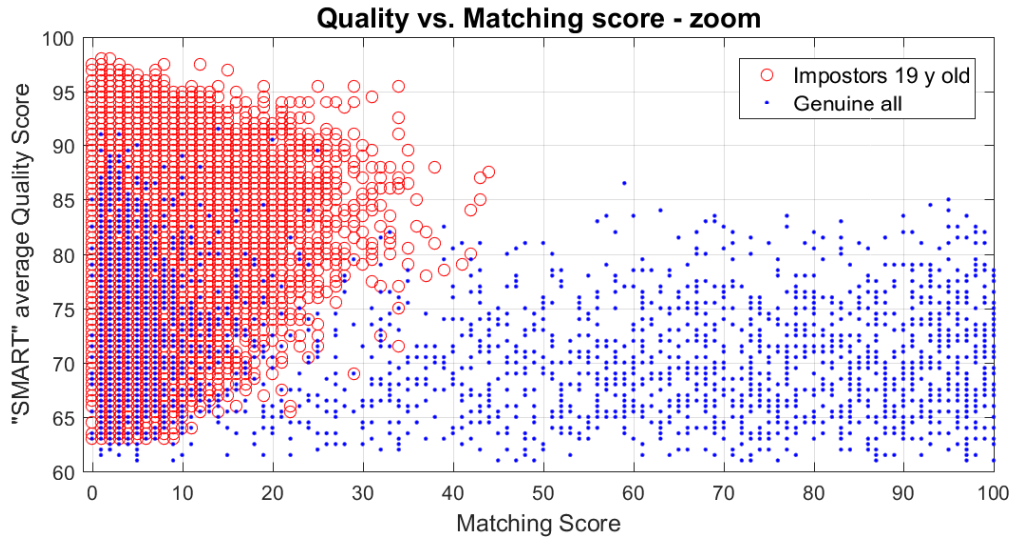

Figure 3 Zoom into the area of interest (x-axis limited to 100)

Zooming into the area of interest Figure 3 allows to better distinguish visually the genuine Matching Score from the impostor Matching Score. However, keeping in mind that the Impostor score distribution is coming from the reference sample, the genuine score distribution was treated as an unsupervised machine learning problem, with the objective to split the genuine score distribution into the genuine / impostor binary classes.

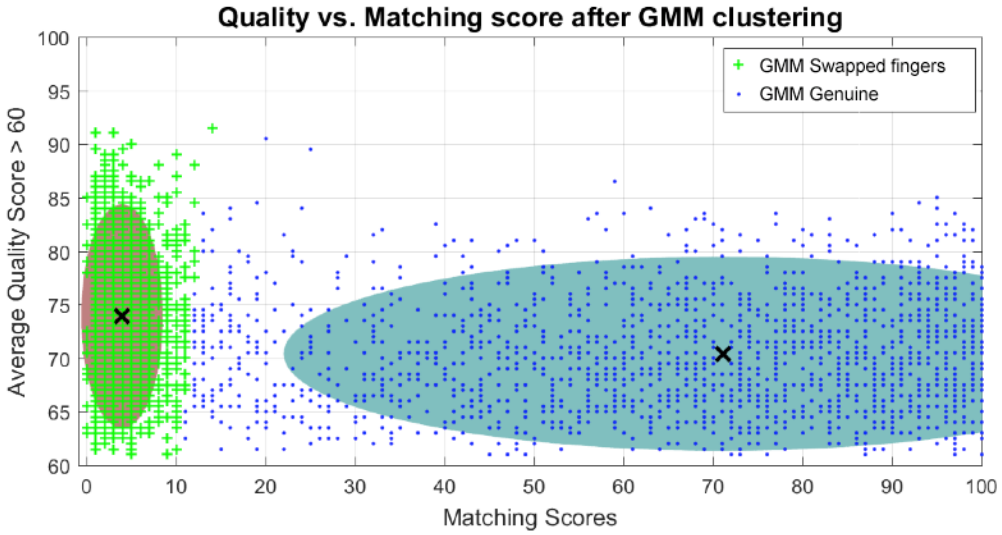

Figure 4 Genuine score distribution split by the GMM into Genuine and Swapped fingers clusters

Although other machine learning algorithms could have been used, knowing that only two possible outcomes were possible - a resulting matching score labelled either as genuine or impostor, and being aware of potential risks of overfitting, we used the Gaussian Mixture Models (GMM) with a diagonal covariance matrix, regularization, random initialization and convergence criteria set to 100 iterations to split the Matching Score distribution into the genuine and swapped fingers (see Figure 4 above).

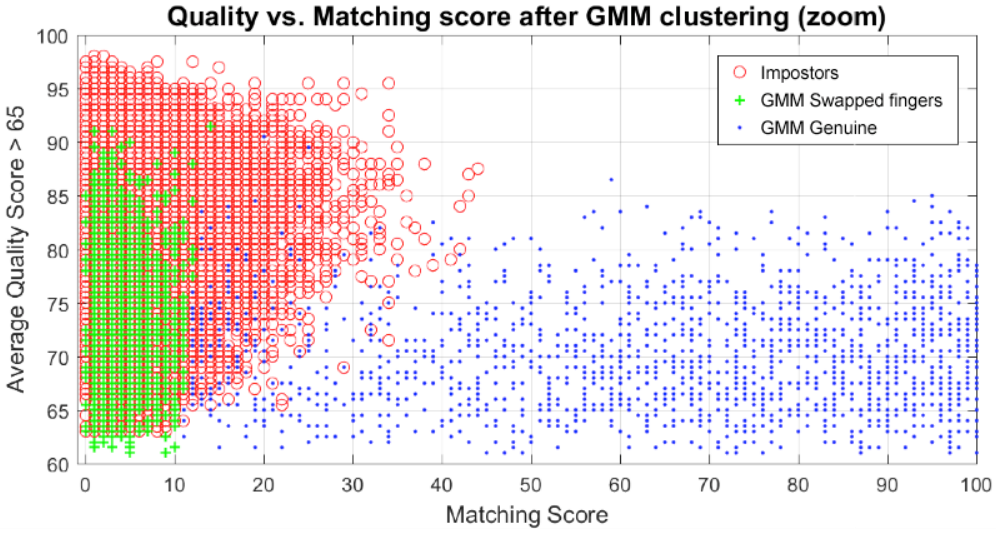

Figure 5 Genuine score distribution split by the GMM into Genuine and Swapped fingers clusters correlated with the Impostor reference sample

Figure 5 above illustrates the distribution of the GMM separated genuine score distribution (blue dots labelled GMM Genuine) from the swapped fingers score distribution (green plus sign labelled GMM Impostors) in correlation with the reference impostor score distribution (red circles labelled Impostors).

In order to visually confirm the results of the GMM clustering, a random sample containing 100 fingerprint pairs was drawn from the swapped fingers score distribution (green plus signs) out of a total of 1892 fingerprint pairs which satisfied the "average NFIQ2 > 60 and under conservative Matching Score <= 15" conditions. All of the randomly drawn samples were indeed swapped or "mislabelled" fingers.

As described in step 4, all potentially swapped fingers have been excluded from the planned scientific experiments. However an extensive ground-truth verification of the pairs of fingers identified as potentially swapped fingers should be conducted latter as these can lead to misidentification of the owner of the fingerprints when checked at the border.

2.2.2 Wrong resolution

Standard operating resolution of the WSQ fingerprint images is 500 DPI. In theory, as long as the fingerprints are of a sufficient quality and the features (e.g. at least the first and second level details) are present in the images, the feature extraction algorithms used should be able to extract minutiae and create templates for matching (see further details about the feature extraction algorithms in Section 3.2).

In the course of the feature extraction and template creation process using Neurotechnology VeriFinger, WSQ images recorded with a wrong resolution were detected in the form of unhandled exceptions. Further analysis has shown that **18,590** fingerprints in the <25 years of age datasets, and **442** fingerprints in the >65 years of age dataset were recorded with a 96 DPI resolution. Upon visual inspection of a number of random samples it was discovered that the quality of the "96 DPI" images and the number of features present in these fingerprints is not inferior to the ones recorded at 500 DPI, which could mean that a "wrong DPI label" was assigned to these images. A decision was therefore taken to "re-encode" these images.

The re-encoding procedure (changing the DPI of the WSQ images from 96 DPI to 500 DPI) entailed **lossless** conversion of the WSQ images to RAW format (number of features, ridges, quality of RAW files is identical to that of the original WSQ image), and a limited **lossy** conversion of the RAW fingerprint back to the WSQ format at the correct 500 DPI resolution (some features / ridge information / quality could be lost in the process)[2].

2.2.3 Duplicated samples

As the previous original dataset received by DG JRC presented some duplicated samples, it was decided to also identify possible ones in the new received dataset.

Duplicated fingerprints, copy-pasted and relabelled identical fingerprint images, were identified based on:

- Both samples belong to the same user
- Both present the identical quality score (NFIQ2),
- Both present the identical physical image size.

For each pair of duplicated samples, one of them was discarded. The result of this action means that these fingers will have FP-1 number[3] of samples in the experiment Database:

- A finger that had FP=1 in the original DATASET, as that sample has been discarded, will not be present anymore in the EXPERIMENTAL DATASET (it will have 0 samples).
- A finger that had FP=2 in the original DATASET, as one of the samples has been discarded, it will only have FP=1 sample in the EXPERIMENTAL DATASET.

The figures corresponding to the discarded duplicated samples were the following:

- Number of duplicated discarded fingerprint samples of persons aged 0-17 years: 8084 (3.06% of the original DATASET)
- Number of duplicated discarded fingerprint samples of persons aged 18-25 years: 2435 (2.09% of the original DATASET)
- Number of duplicated discarded fingerprint samples of persons aged 65 years and above: 349 (0.62% of the original DATASET)

[2] According to the FBI specifications the NBIS software used resulted in 15:1 RAW to WSQ compression
[3] The total number of samples FP that they had in the original DATASET, minus the sample that is being discarded

Eventually, the total number of duplicated fingerprint samples discarded was: **10868 (2.49% of the original database)**

Details 0-17 (Children):

#FPs per finger in original dataset	***SAMPLES DISCARDED from the DATASET that belong to a finger with #FPs in the original dataset***
1	2038
2	5716
3	273
4	52
5	5
6	0
7	0
TOTAL	8084

Details 18-25 (Adults):

#FPs per finger in original dataset	***SAMPLES DISCARDED from the DATASET that belong to a finger with #FPs in the original dataset***
1	1716
2	704
3	15
4	0
5	0
6	0
7	0
TOTAL	2435

Details 65-98 (Elderly):

#FPs per finger in original DATASET	***SAMPLES DISCARDED from the DATASET that belong to a finger with #FPs in the original DATASET***
1	57
2	268
3	21
4	2
5	1
6	0
7	0
TOTAL	349

2.2.4 No pattern recorded

Last step in the cleaning procedure involved the analysis of the WSQ fingerprint files which failed to produce a fingerprint template. Presenting an extremely low quality score, a number of fingerprints were detected from which the VeriFinger feature extractor failed to produce a template.

This category of errors does not consider the "ghost" fingerprints and dry or partial fingerprints. In the <25 datasets, 4 individuals were detected (finger number 2 and finger number 7 – e.g. in total 8 fingerprint records), for which the fingerprint record shows ***NO*** pattern at all. The fingerprint in these cases visually corresponds to a scan of a "white paper". Here we operate under the assumption, that there is a procedure in place, which enables recording of consecutive fingers in cases where the index fingers are missing.

Using the NFIQ2 quality measure, further **2** individuals, one fingerprint per individual, with no recorded pattern were detected in the >65 dataset.

2.3 Experimental Dataset

Once the mistakes described above have been addressed, to the extent of available resources of the team, we produced a final data-set which presents the following figures:

Total number of different fingers used in the experiments: **265,341**

- Children (0-17 years): 147,758
- Adults (18-25 years): 78,520
- Elderly (65-98 years): 39,063

These fingers have produced the following number of fingerprint samples:

- Children (0-17 years): 253,457
- Adults (18-25 years): 116,588
- Elderly (65-98 years): 56,291

Total number of fingerprint samples used in the experiments: **426,336**

The figures above are further detailed in the next tables:

Details CHILDREN 0-17:

#FPs impression per finger	*#fingers*	*#FPs*
1	45158	45158
2	99649	199298
3	2821	8463
4	115	460
5	12	60
6	3	18
7	0	0
TOTAL	147758	253457

Details ADULTS 18-25:

#FPs impression per finger	*#fingers*	*#FPs*
1	41992	41992
2	35205	70410
3	1146	3438
4	149	596
5	20	100
6	4	24
7	4	28
TOTAL	78520	116588

Details ELDERLY 65-98:

#FPs impression per finger	*#fingers*	*#FPs*
1	22104	22104
2	16738	33476
3	192	576
4	20	80
5	3	15
6	4	24
8	2	16
TOTAL	39063	56291

An important figure that can be extracted from the tables above is that the database contains a total 156,087 fingers with 2 or more samples (102,600 belonging to the children,

36,528 belonging to adults and 16,959 belonging to the elderly). All of these fingers can be used to obtain the genuine matching scores (comparing their two respective samples).

The number of fingers with 3 or more samples is very limited, thus for all the 156,087 fingers with 2 or more samples, only the first and last samples (called here after: S.a and S.b) will be considered, leading to 156,087 fingerprint pairs. The time difference between the S.a and S.b for these fingerprints pairs is as follows:

	NUMBER OF FINGERPRINT PAIRS							
	Time difference between S.a and S.b (years)							
	0-1	**1-2**	**2-3**	**3-4**	**4-5**	**5-6**	**6-7**	**7-8**
CHILDREN (0-17)	565	1842	12891	7842	15226	49716	13090	1426
ADULTS (18-25)	1613	3525	2842	2193	7101	16012	2657	146
ELDERLY (65-98)	596	812	623	537	3007	10420	961	3

Table 1 Number of fingerprint pairs according to the time difference between S.a and S.b samples.

Number of fingerprint pairs according to the time difference between S.a and S.b samples.

A more detailed year-by-year distribution of the fingerprint pairs is given in Annex 2.

The age distribution of the fingerprint samples in the database is as shown in Figure 6, Figure 7 and Figure 8:

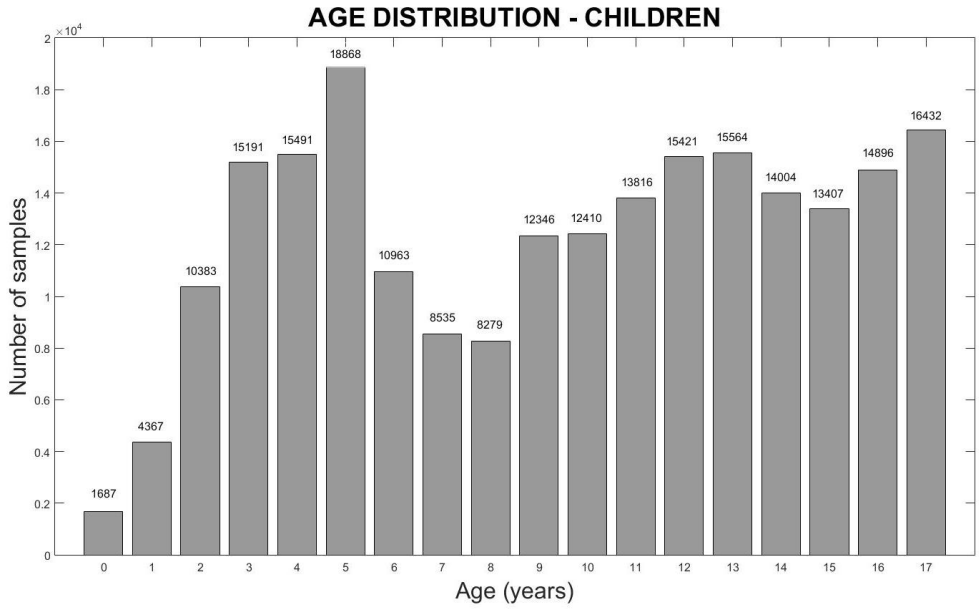

Figure 6 Age distribution of the samples contained in the experimental dataset for the children group, ages 0-17. For each age, the total number of samples is given.

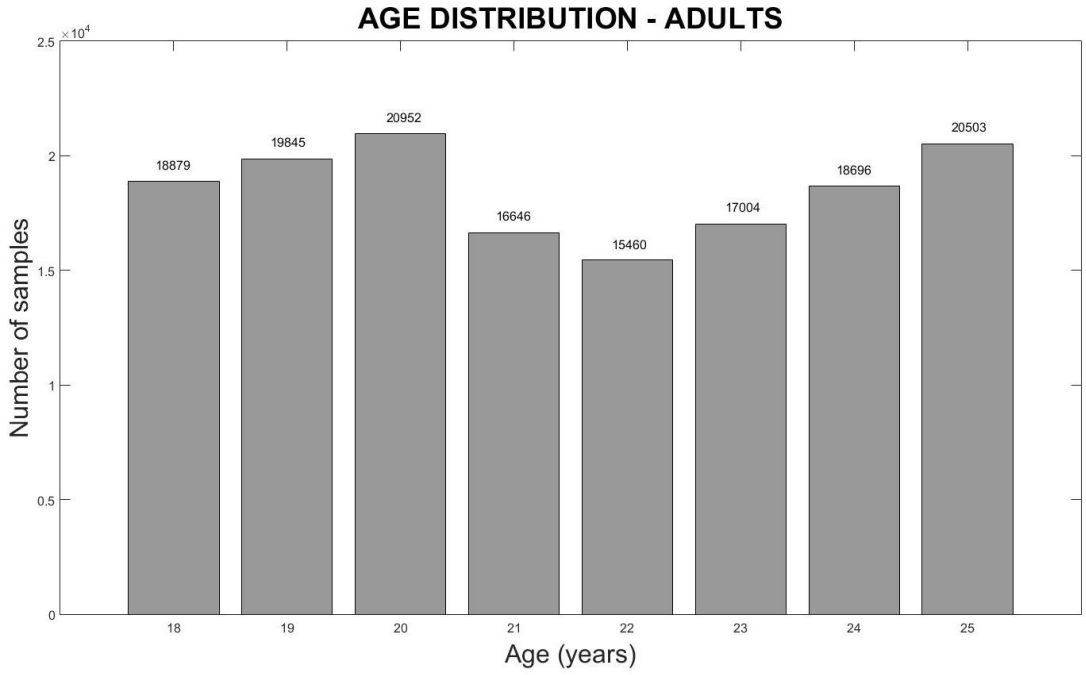

Figure 7 Age distribution of the samples contained in the experimental DATASET for the adults group, ages 18-25. For each age, the total number of samples is given.

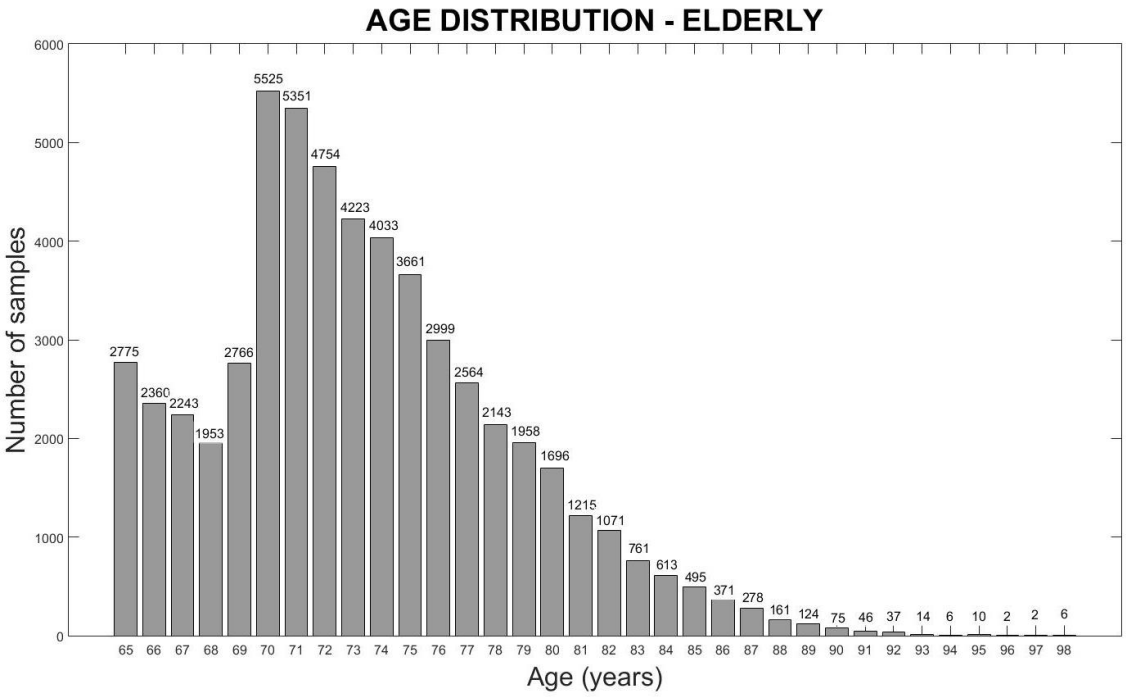

Figure 8 Age distribution of the samples contained in the final experimental DATASET for the elderly group, ages 65-98. For each age, the total number of samples is given.

Further detailed features of the experimental dataset can be found in Annex 2.

3 Experimental protocol

3.1 Security

The reception of the data implied the appropriate implementation of a number of security and data protection related requirements, as set out in the Security Plan defined at the beginning of the cooperation agreement.

The security plan is based on the following elements:

- As defined in Article 2 of the agreement signed with the Immigration and borders Service of Portugal, the disclosure of the data has the sole purpose of performing a scientific research on the technical possibility and feasibility of using/reading fingerprints collected from persons from the afore-mentioned age groups, for purposes of identifying an individual.
- The current dataset is linked to the same data protection notification as the first dataset (used in the 2013 DG JRC Report). Following recommendations from the European Data Protection Supervisor, this notification has been updated in order to take into account the new age groups included (adults and elderly)[4] .

Thus, the security plan reuses to a large extent the methodologies, security concepts, safeguard measures and tools as described in the 2013 JRC report "Fingerprint Recognition for Children" [1].

3.2 Software tools

The evaluation of the performance of feature extraction applications and matching algorithms selected for the experiments are not the subject of the study. Thus, their comparison with the state-of-the-art in the domain of fingerprint identification was not one of the selection criteria, as the aim was to confirm the age/quality hypotheses and observation of trends, e.g. improving quality of the fingerprints with age amongst kids and adolescents, decrease in quality amongst the fingerprints of the elderly. For this purpose, the performance of the matching algorithms was considered satisfactory for the purpose of the study and the results obtained by either of the matching algorithms confirmed the same expected trends.

The main selection criteria of the fingerprint feature extraction and matching algorithms were:

- Availability: NIST NBIS / Bozorth3 are available as open source and Neurotechnology VeriFinger/MegaMatcher available under license.
- Scalability: open source in the case of NBIS/Bozorth3 and the SDK of the VeriFinger /MegaMatcher obtained under license, allowed for development of customized (purpose built) scripts.
- Vendor support: both systems were supplied with large and sufficient amount of documentation, and in the case of Neurotechnology, virtually real-time feedback provided by the vendor was proven very useful at times.

3.2.1 Quality Metric Algorithms

3.2.1.1 NEUROTECHNOLOGY

This proprietary fingerprint quality evaluation metric (called hereafter VERIQ) returns values between 0 and 255. According to the Neurotechnology support team, the quality

[4] DPO-3332.2 - JRC : Fingerprint Recognition Study

metric values between 200-255 should correspond to the NFIQ values of 1 (Excellent) and 2 (Very Good).

3.2.1.2 NIST NFIQ2

The development of NFIQ2 was driven by the progresses accomplished in fingerprint technology since the original version of the NFIQ was published in 2004 [8]. It was initiated in 2011 by the US NIST (National Institute for Standards and Technology), the German BSI (Bundesamt fur Sicherheit in der Informationstechnik), the German BKA (Bundeskriminalamt) and other R&D partners. The major differences in comparison with the original NFIQ are:

- The increased sensitivity range to 0-100 (according to the ISO/IEC 29794-1:2016), where 100 represents excellent quality and 0 very poor quality; and
- Lower complexity as NFIQ2 quality features are being formally standardized as part of the ISO/IEC 29794-4 Biometric Sample Quality [9].

Alike NFIQ, the NFIQ2 is also supplied as an open-source platform with re-training possibilities and the potential to develop "tailor-made" solutions (e.g., specific NFIQ2 version for children/elderly and or fingermarks/latent fingerprints).

It should be noted, that the distributable version of NIFQ2 has been trained using solely adult fingerprint data acquired with live-scan optical sensors at 500 dpi resolution.

3.2.2 Matchers algorithms

3.2.2.1 NIST - NBIS (bozorth3)

NIST Biometric Image Software (NBIS)[5] was developed by the NIST for the Federal Bureau of Investigation (FBI) and the Department of Homeland Security (DHS). The NBIS feature extraction (MINDTCT) and matching algorithm (bozorth3) is freely distributed and not subject to licensing requirements. The MINDTCT minutiae detector automatically detects and extracts fingerprint minutiae from the input WSQ image, while the minutiae-based fingerprint matching algorithm BOZORTH3 is used to perform 1:1 or 1:N matching. One advantage of using the NBIS feature extraction and matching algorithms is the fact, that the fingerprint template is produced in a non-proprietary format with the location and orientation of the minutiae immediately accessible.

3.2.2.2 NEUROTECHNOLOGY – VeriFinger (MegaMatcher)

VeriFinger (Version 10.0 of the NEUROTECHNOLOGY feature extraction and matching algorithm), based on the MegaMatcher identification engine and compliant with NIST MINEX [10], is used in addition to the NBIS software. The feature extraction and matching algorithm uses minutiae points and a number of non-specified "proprietary algorithmic solutions", which enhance the performance and reliability of the system. The feature extraction algorithm produces the template in a NEUROTECHNOLOGY proprietary format (access to minutiae points is available through the NEUROTECHNOLOGY SDK) and like the BOZORTH3, the VeriFinger matching algorithm can perform 1:1 or 1:N matching [11].

3.3 Experimental protocol

The way time affects the accuracy of biometric systems in general, and fingerprint recognition systems in particular, can be seen from two different angles depending on whether the focus is: 1) the effects of age of the enrolled template (age effect) during the lifetime of an individual, or whether it is on 2) the effects of time difference between two

[5] *https://www.nist.gov/services-resources/software/nist-biometric-image-software-nbis*

fingerprint samples enrolled in two different times (ageing effect). These two effects can be defined as follows:

- Age effect: refers to the variation of accuracy of fingerprint recognition systems due to the age of the individual and his/her enrolled templates (considering that the test template was acquired shortly after the enrolled template). For instance, the age effect will account for quality and accuracy differences between children, adults and elderly.
- Ageing effect: refers to the variation of quality and accuracy of fingerprint recognition systems as a result of an increasing time difference between the two enrolled templates of the same individual (e.g., the time difference between the fingerprint stored in the chip of the passport and the test one from the same individual when (s)he crosses a border).

A diagram summarizing these two effects is depicted in Figure 9. Of course, age and ageing are not independent. For example, ageing may impact differently children, adults and elderly as it will be demonstrated later in the report. However, studying both effects in experiments as decoupled from each other will contribute to analyse and to better understand how time affects biometric systems and, eventually, to mitigate its effects whenever possible.

It should also be noted that both, age and ageing, have an impact by definition, on the genuine scores, that is matching scores resulting from the comparison of two samples of the same finger.

The experimental protocol has been designed to study these two effects. Accordingly, it comprises two main sets of experiments directed to analyse the age effect (Section 3.3.1); and focused on analysing the ageing effect (Section 3.3.2).

Additionally, a third set of experiments (Section 3.3.3) has been carried out in order to estimate the way in which children fingerprints grow and whether a growth model can be used to mitigate, to some extent, any of the previous effects (i.e., age and ageing) in order to eventually preserve the accuracy offered by systems.

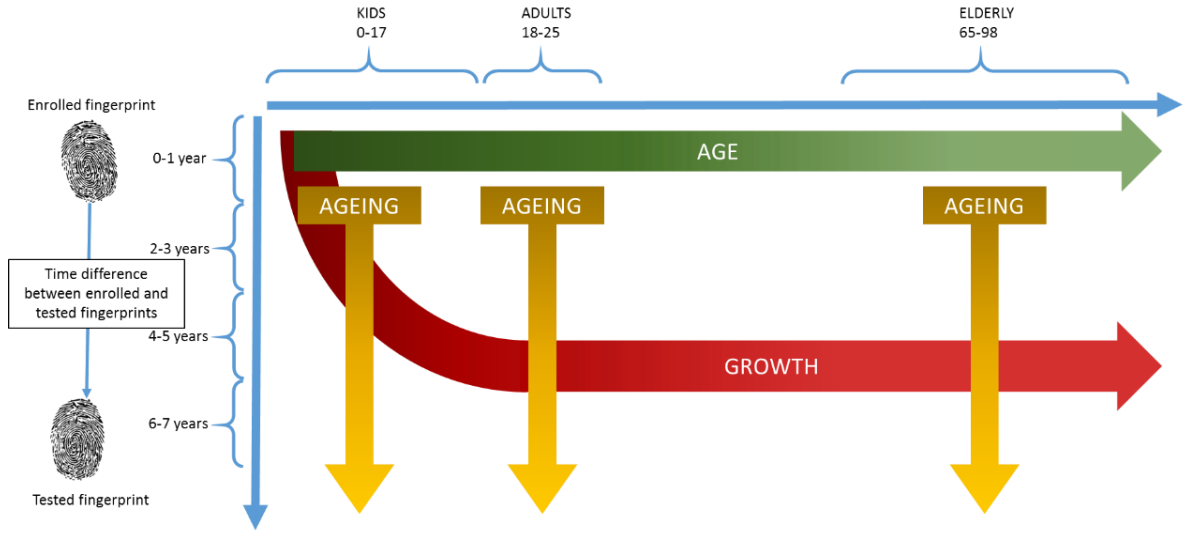

Figure 9 Diagram showing the two different effects that time has on the accuracy of biometric systems: the age effect and the ageing effect.

3.3.1 Age effect

The age effect is studied from two intertwined points of view: quality and matching (genuine) scores [8]. The objective is to demonstrate if the age of the individual can play a role in the performance of biometric systems.

3.3.1.1 Quality

The quality of all the 426,336 samples present in the experimental dataset is extracted using the two metrics considered: NFIQ2 and VERIQ (see Section. 3.2.1 for a description of these metrics).

Samples are first classified according to their age in three different groups: children (age 0-17), adults (age 18-25) and elderly (age 65-98). Quality distributions for each of the three groups are computed.

The children group is then divided into 3 sub-groups: 0-4, 5-12, 13-17. The quality distributions of each of these sub-groups are computed.

The elderly group is divided into 4 sub-groups: 65-69, 70-74, 75-79, 80-98. The quality distributions of these sub-groups are also computed.

Finally, the mean quality value per year of age (i.e, mean quality value for age 1, 2, 3,… 98) is also computed.

This experimental protocol is depicted in Figure 10.

Results are presented in Section 4.1.1.

3.3.1.2 Matching

Biometric quality metrics are generally understood as a way to estimate or predict the performance of a given sample when used for recognition purposes. This is the case of the two fingerprint quality metrics considered in this study, NFIQ2 and VERIQ. Therefore, in order to confirm the results obtained in the previous quality-related experiments, genuine similarity scores were produced using the two matching systems considered: VeriFinger and NIST/NBIS (see Section. 3.2.2 for further details on these systems).

Since biometric quality and accuracy are closely interdependent, the objective of the matching experiments was to determine to what extent quality metrics are capable of reflecting the variations in accuracy of fingerprint recognition systems.

In order to be able to compute genuine matching scores, for these experiments, only those fingers with more than one fingerprint sample in the database were considered. Therefore, all fingers with just one sample were discarded.

Since the number of fingers in the database with more than two samples is very limited, in these cases only the first and last fingerprint sample (from timeline point of view) of the finger were taken into account.

In order to analyse (only) the age effect, fingers offering the smallest time between the enrolled and test samples were favoured. However, taking only sample pairs (enrolled-test) that were acquired for instance on the same year, would reduce drastically the available data and possibly undermine the statistical relevance of the results. As such, a compromise had to be reached between: proximity of the enrolled and test samples and amount of available data.

Following this necessary compromise, in the end, 87,011 fingerprint pairs were used in the experiments, which generated as many genuine scores divided as follows:

NUMBER OF GENUINE MATCHING SCORES - KIDS																	
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
812	2383	7130	9041	243	229	203	166	187	186	167	250	295	5105	5104	5158	5293	5830

NUMBER OF GENUINE SCORES - ADULTS							
18	**19**	**20**	**21**	**22**	**23**	**24**	**25**
7142	7605	9291	4172	2136	1712	1228	439

NUMBER OF GENUINE SCORES - ELDERLY																			
65	**66**	**67**	**68**	**69**	**70**	**71**	**72**	**73**	**74**	**75**	**76**	**77**	**78**	**79**	**80**	**81**	**82**	**83**	**84**
908	653	621	460	416	361	308	275	253	220	220	169	143	99	113	91	68	61	35	30

Table 2 Number of genuine scores computed for the age-related experiments. Number of genuine scores computed for the age-related experiments.

Since the number of pairs above 85 years of age was very scarce, they were not considered in the experiments.

As for the quality-related experiments, the 87,011 genuine scores were divided in three different groups: children (age 0-17), adults (age 18-25) and elderly (age 65-85). The distributions for each of the three groups were computed.

The children group is divided into 3 sub-groups: 0-4, 5-12, 13-17. The genuine score distributions of each of these sub-groups are computed.

The elderly group is divided into 4 sub-groups: 65-69, 70-74, 75-79 and 80-84. The genuine score distributions of these sub-groups are also computed.

Finally, the mean genuine score value per year of age (i.e, mean genuine score value for age 1, 2, 3,… 84) is also computed.

The complete experimental protocol for the age-related experiments is depicted in Figure 10.

The main results are presented in Section 3.3.1 while supplementary results are given in Annex 3.

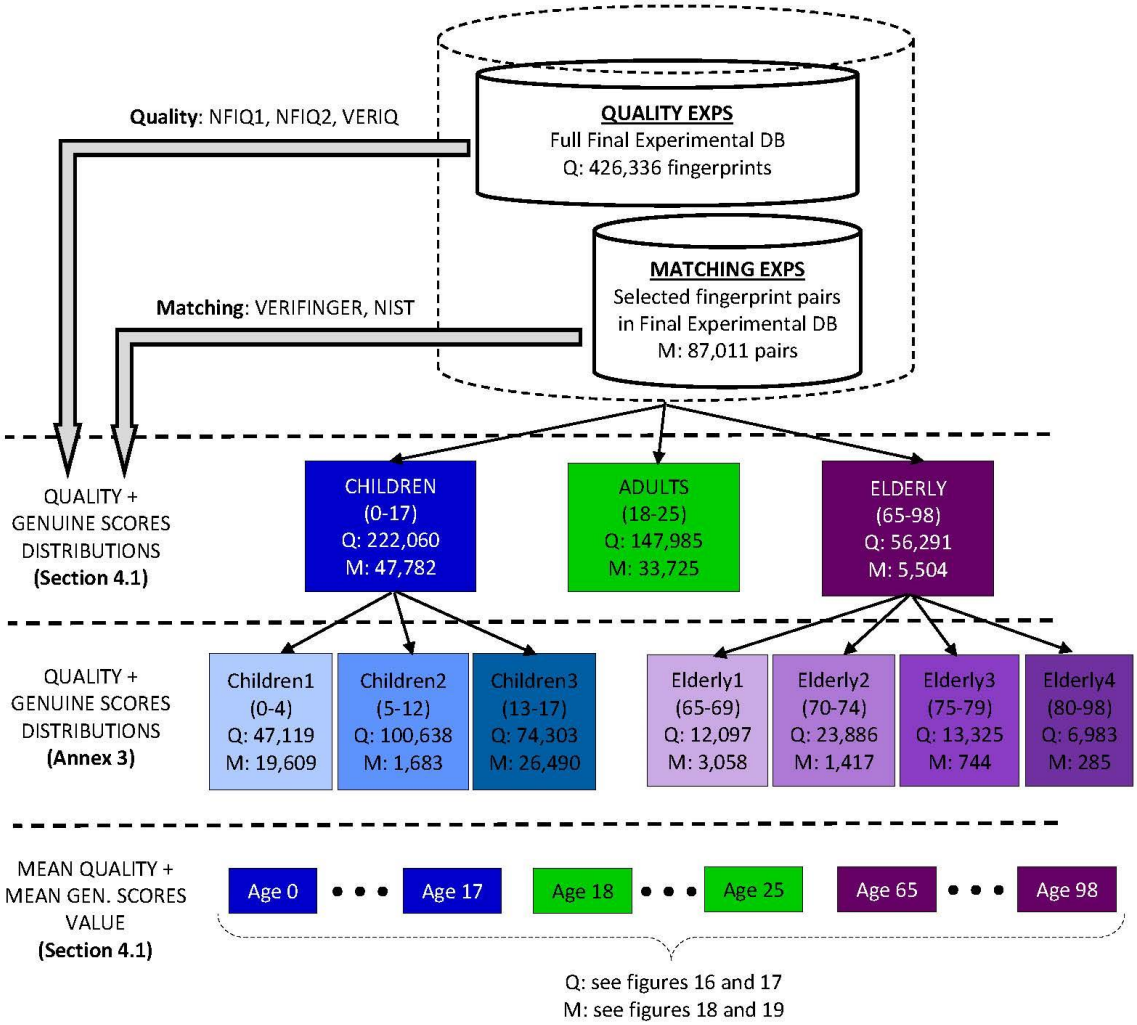

Figure 10. Protocol followed for the quality-related and matching-related experiments carried out to study the age effect.

3.3.2 Ageing effect

Individuals will interact with biometric systems over the course of their entire lives. This way, it can happen that their biometric data is verified against a sample which was enrolled several years before. The objectives of these experiments are therefore twofold:

- Estimate the matching score variation of fingerprint verification systems when the time difference between the enrolled fingerprint and the test fingerprint increases. That is, estimate the level of Matching score degradation due to time changes in the genuine population (population which is enrolled to the system).

- Determine, if the matching score degradation is different depending on the age of the individual.

The experiment population on which the matching process is applied contains all 156,067 fingers with 2 fingerprint samples in the dataset. The first sample is used as the enrolled sample and the second one as the test sample. In the case of fingers with 3 or more samples, only the first sample (enrolled) and the last sample (test) offering the biggest time difference are considered in the experiments.

As in the case of the age-effect experiments, eight different age-groups will be considered for the genuine population and each finger will be assigned to one of the groups according to the age at which the first fingerprint sample was enrolled in the system:

- Children1 0-4
- Children2 5-12
- Children3 13-17
- Adults 18-25
- Elderly1 65-69
- Elderly2 70-74
- Elderly3 75-79
- Elderly4 +80

Each of these age groups will be then further divided into 8 sub-groups, according to the time difference between the enrolled and the test sample as explained below.

The protocol applied to age group "adults 18-25" will serve as a baseline (in green in

Table 3). Then, the matching scores for the rest of the age groups will be processed under the same protocol and compared against it.

The evolution of the matching scores provided by VERIFINGER and NIST algorithms will be evaluated for eight different sub-cases, depending on the time difference between the enrolled sample and the test sample. These eight sub-cases are:

- Less than 1 year difference. This case covers all fingers of the genuine population whose first sample was acquired when the user was between 18 and 25 years, and its second sample was acquired less than one year later.
- Between 1 and 2 years difference. This case covers all fingers of the genuine population whose first sample was acquired when the user was between 18 and 25 years of age, and its second sample was acquired between 1 and 2 years later.
- Etc.
- Between 7 and 8 years difference. This case covers all fingers of the genuine population whose first sample was acquired when the user was between 18 and 25 years of age, and its second sample was acquired between 7 and 8 years later.

Accordingly, for the adult category (and for all the other age group categories as well) there will be eight different sets of genuine scores. One pair for each of the cases described above.

The result of the complete set of experiments will be constituted by 64 sets of genuine scores6. In the experiments, a total 156,067 genuine scores are computed (both for the VERIFINGER and the NIST matchers), divided among each of the 64 sub-sets as specified in table 3.

[6] 64 = 8 age-groups (enrolled sample = [0-4, 5-12, 13-17, 18-25, 65-69, 70-74, 75-79, 80+]) x 8 time differences (test sample = [<1 year, 1<2, 2<3, 3<4… 7<8]).

Age-group	NUMBER OF GENUINE SCORES							
	Time difference between enrolled and test samples (years)							
	0-1	**1-2**	**2-3**	**3-4**	**4-5**	**5-6**	**6-7**	**7-8**
0-4	69	1072	11881	6587	4725	5378	1677	280
5-12	249	381	444	609	5323	24874	6466	607
13-17	247	389	566	646	5178	19464	4947	539
18-25	1613	3525	2842	2193	7101	16012	2657	146
65-69	299	449	319	330	1661	5698	515	
70-74	147	181	177	124	788	3134	261	
75-79	91	99	78	57	419	1217	134	
80-98	47	77	41	26	135	349	42	

Table 3 Number of genuine scores for each of the 64 sub-groups considered for the ageing experiments.

The analysis proposed for the ageing effect will be done using the score distributions and the evolution of the mean score of these distributions. Main results are presented in Section 4.2 while complementary results can be checked in Annex 4.

A diagram summarizing the experimental protocol for the aging experiments is shown in Figure 11.

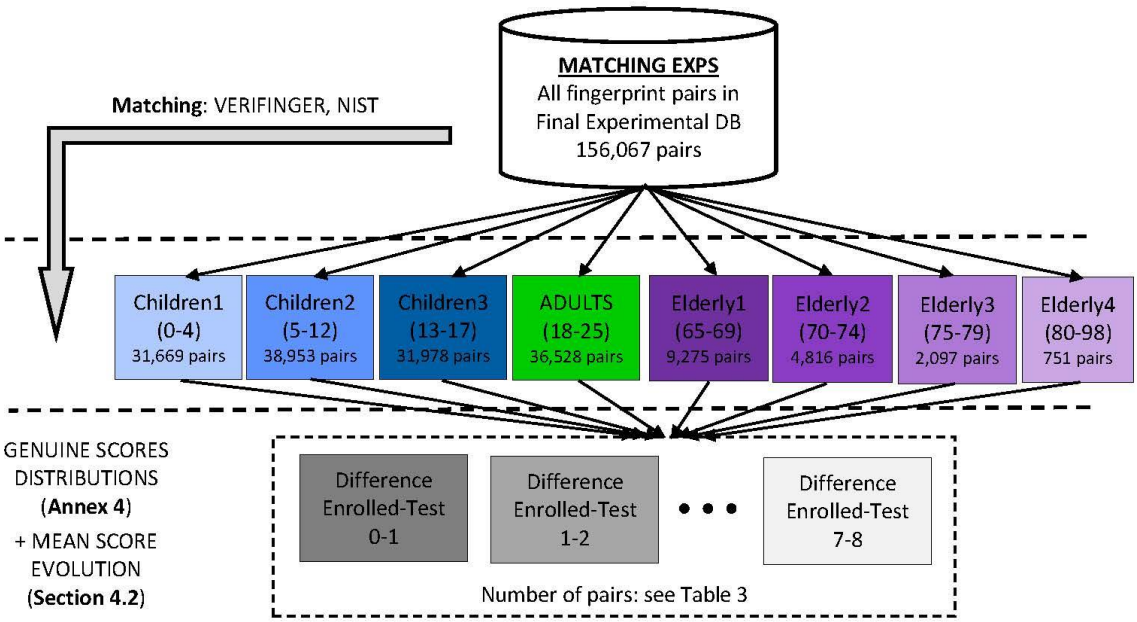

Figure 11 Protocol followed for the experiments carried out to study the ageing effect.

3.3.3 Growth model

Out of the final dataset, 105 genuine pairs of fingerprints were selected based on the age at first enrolment (5-year olds), the time difference between the enrolment of the fingerprints (7 categories) and the average fingerprint-pair quality (highest possible quality). The test dataset for the development of the growth model is presented in detail below in Table 4.

Category	Age at enrolment sample T0	Time difference between enrolled samples T0 and T1	Number of fingerprint pairs
I	5	0 years	15
II	5	1 years	15
III	5	2 years	15
IV	5	3 years	15
V	5	4 years	15
VI	5	5 years	15
VII	5	6 years	15

Table 4 Growth model development dataset

The growth model is based on the pixel-wise distances, measured between the centre of origin and the coordinates of selected minutiae points. Neurotechnology automatic fingerprint feature extractor was used to provide a list of matching minutiae points between the pair of fingerprint images. These minutiae points were subsequently verified using a Neurotechnology SDK based purpose-built JRC application (interface is shown in Figure 12 below) and subjected to a manual selection procedure which had two purposes:

- First the centre of fingerprint was manually selected, mainly due to the fact that the centre of origin coordinates provided by Neurotechnology could not be pinpointed to a particular point (be it a singularity point such as core / delta, or an existing minutiae).
- Subsequently 12 minutiae points were selected, giving preference to the matching pairs on the periphery of the fingerprint as this is the part of the fingerprint where the least amount of distortion may be found [12], [13].

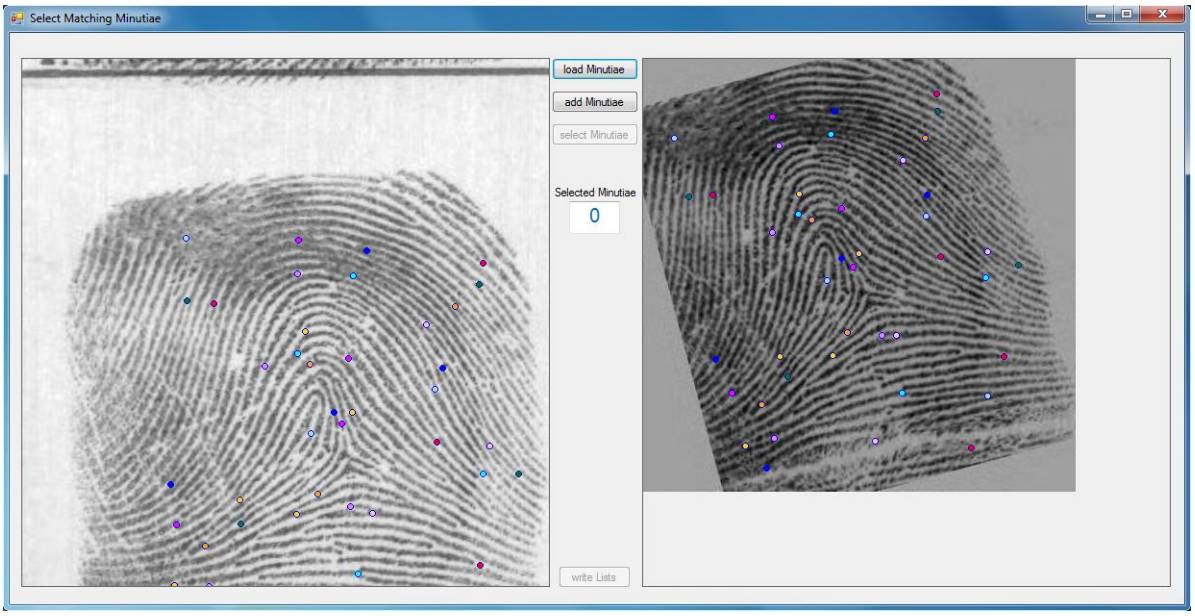

Figure 12 JRC Minutiae selection application

The minutiae selection/validation process was completed by three different "examiners" (35 pairs of fingerprints each). Subsequent post-processing, namely the manual establishment of the centre of the fingerprint pairs as the centre of origin, translation of the coordinates of remaining minutiae points and the rotation of the images provided excellent starting point. An example shown in Figure 13

below shows a set of super-imposed minutiae points, which illustrates approximate representation of the dataset in order not to reveal any personal information [1].

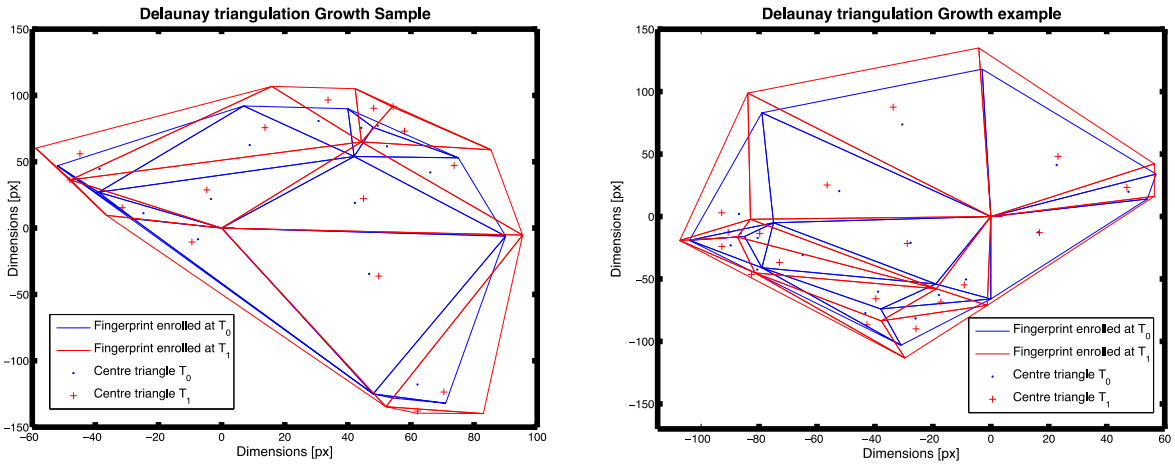

Figure 13 Delaunay triangulation of the superimposed minutiae points (Vertices of the triangles) indicate the growth of the finger.

The pixel-wise distances measured from the super-imposed images are used to compute the coefficients of a growth model for each age group, which will be applied to the test sample in a process depicted in Figure 14 below.

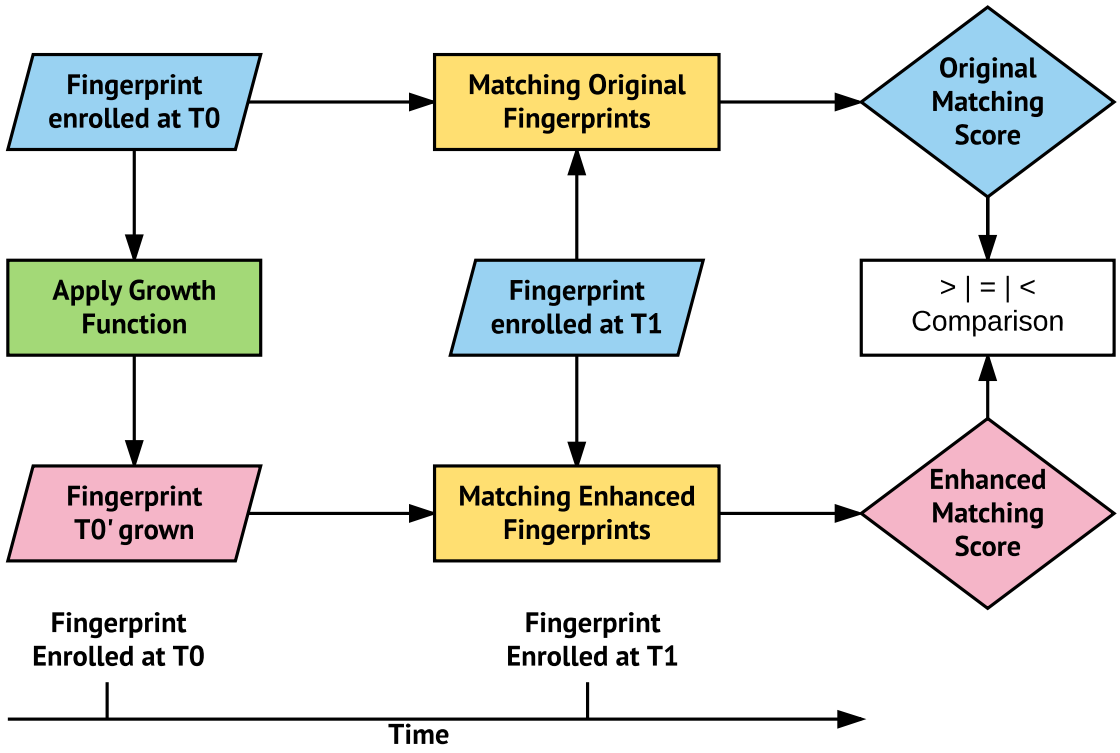

Figure 14 application of the growth model to the test data

First the growth function for a respective category, which is determined by the temporal difference between the T0 and T1 fingerprints as well as the age of enrolment of fingerprint T0, will be applied to the fingerprint enrolled at time T0 producing the fingerprint T0'. Then the same matching algorithm will be used to compare the fingerprints T0 and T0' to their corresponding fingerprint T1 enrolled in later stage. Finally, the matching scores will be compared. It is expected that a higher matching score should be observed for the pair T0' and T1, as this matching pair corresponds to the scenario of comparison of two fingerprint samples enrolled within a very short time-frame.

In the validation stage, the same growth model is used to rejuvenate the fingerprints enrolled at the time T1. As in the case of growth of the fingerprints, the inverse growth function is applied to the fingerprints enrolled at the time T1, which produces the rejuvenated fingerprint T1'. The rejuvenated fingerprint is then compared to the original fingerprint captured at the time T0. The entire procedure is depicted below in Figure 15.

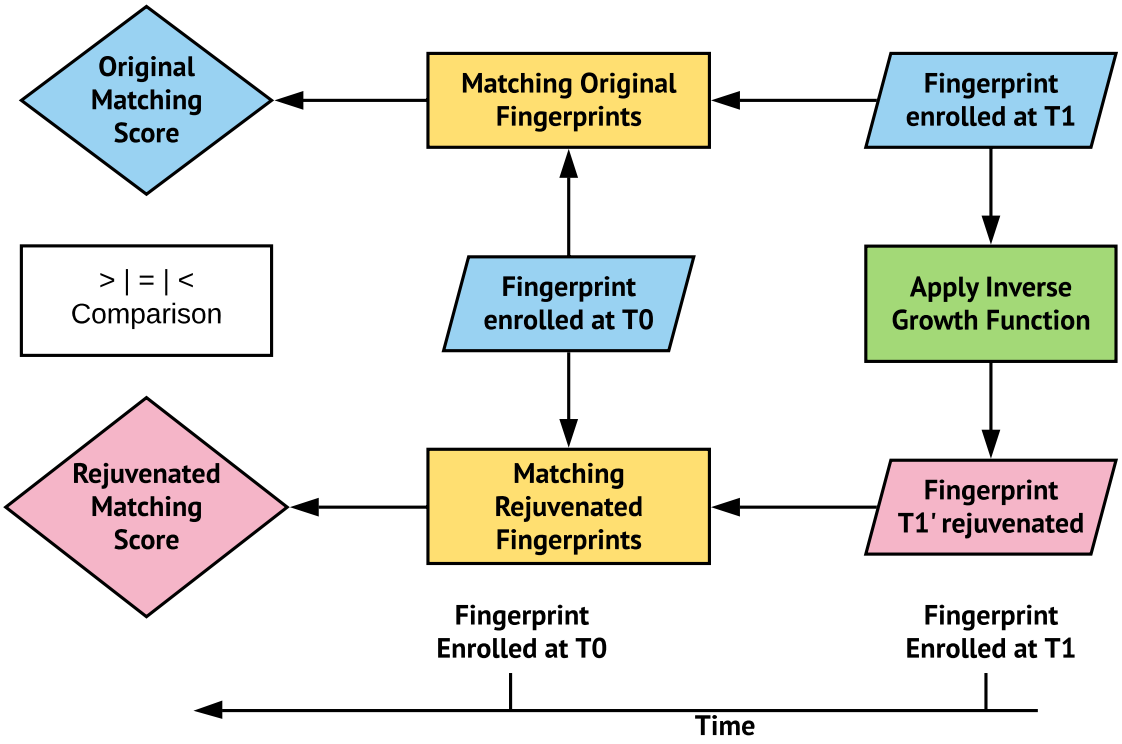

Figure 15 application of the growth model to rejuvenate the test data

4 Results of the experiments

The protocol described in Section 3 contains a large number of experiments that have produced multiple results. For the sake of clarity, only the key figures from which the main conclusions of the study may be drawn have been kept in the present section. Detailed results that complement these main findings can be consulted in Annexes 3 and 4 at the end of the document.

4.1 Age effect

The results presented in the next subsections have been obtained following the experimental protocol described in Section 3.3.1.

4.1.1 Age effect: Quality

Figure 16 shows the comparison of the fingerprint quality distributions of the three overall age groups in the final experimental dataset: children, adults and elderly. Quality scores have been obtained with NFIQ2 (top) and VERIQ (bottom), we refer the reader to Section 3.2.1 for further details on these two quality metrics.

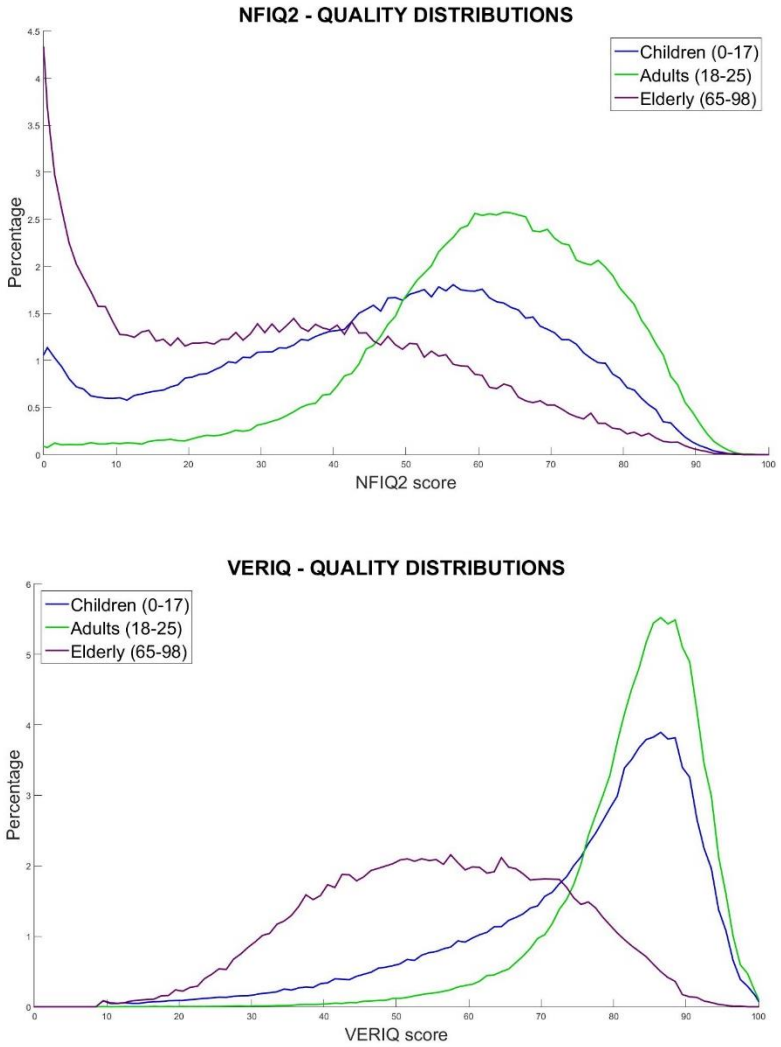

Figure 16 Comparison of the children, adults and elderly fingerprint quality according to NFIQ2 (top) and VERIQ (bottom).

Given that the fingerprint data in the experimental dataset are not uniformly distributed age-wise (see Figure 6, 7 and 8), the quality distributions shown in Figure 16 should not be taken as a perfect reflection of reality. However, given the amount of data considered, these distributions do reflect the general trend that can be expected from fingerprint data in these three large age-groups (children, adults and elderly). As such, it is safe to extract the next conclusion from the results shown in Figure 16:

FINDING 1.

In terms of fingerprint quality, the most challenging age-group is the elderly (65 years of age and above), which presents an overall quality significantly lower than that of children (0-17 years of age). As could be expected, adults clearly present the highest fingerprint quality.

For further details that confirm the conclusion stated above, the reader can go to Annex 3 for the quality distributions of the different subgroups considered within the children and elderly groups: children1 (0-4), children2 (5-12), children3 (13-17), elderly1 (65-69), elderly2 (70-74), elderly3 (75-79) and elderly4 (80-85).

Figure 17 shows the year-by-year evolution of the mean fingerprint quality in the final experimental dataset. The 90% confidence intervals for each of the mean values are shown as vertical red lines.

For those ages not present in the dataset, that is, ages between 26 and 64 (plotted in light grey in Figure 17), the mean fingerprint quality has been estimated using values for ages 18-25 (plotted in green) and 65-90 (plotted in purple).

Given the low number of adult values (only eight, 18-25), the mean quality value of ages 26-43 has been estimated as the average of the mean quality values in ages 18-25 (horizontal red hashed line). Such an estimation follows the hypothesis that in adult life, fingerprint quality should not vary significantly.

For ages 43-64, the mean quality values have been estimated with a linear Least Squares fit using mean quality values 65-90. Mean quality values corresponding to ages 91-98 have not been used for the estimation as they are not reliable enough (as shown by the size of the 90% confidence intervals).

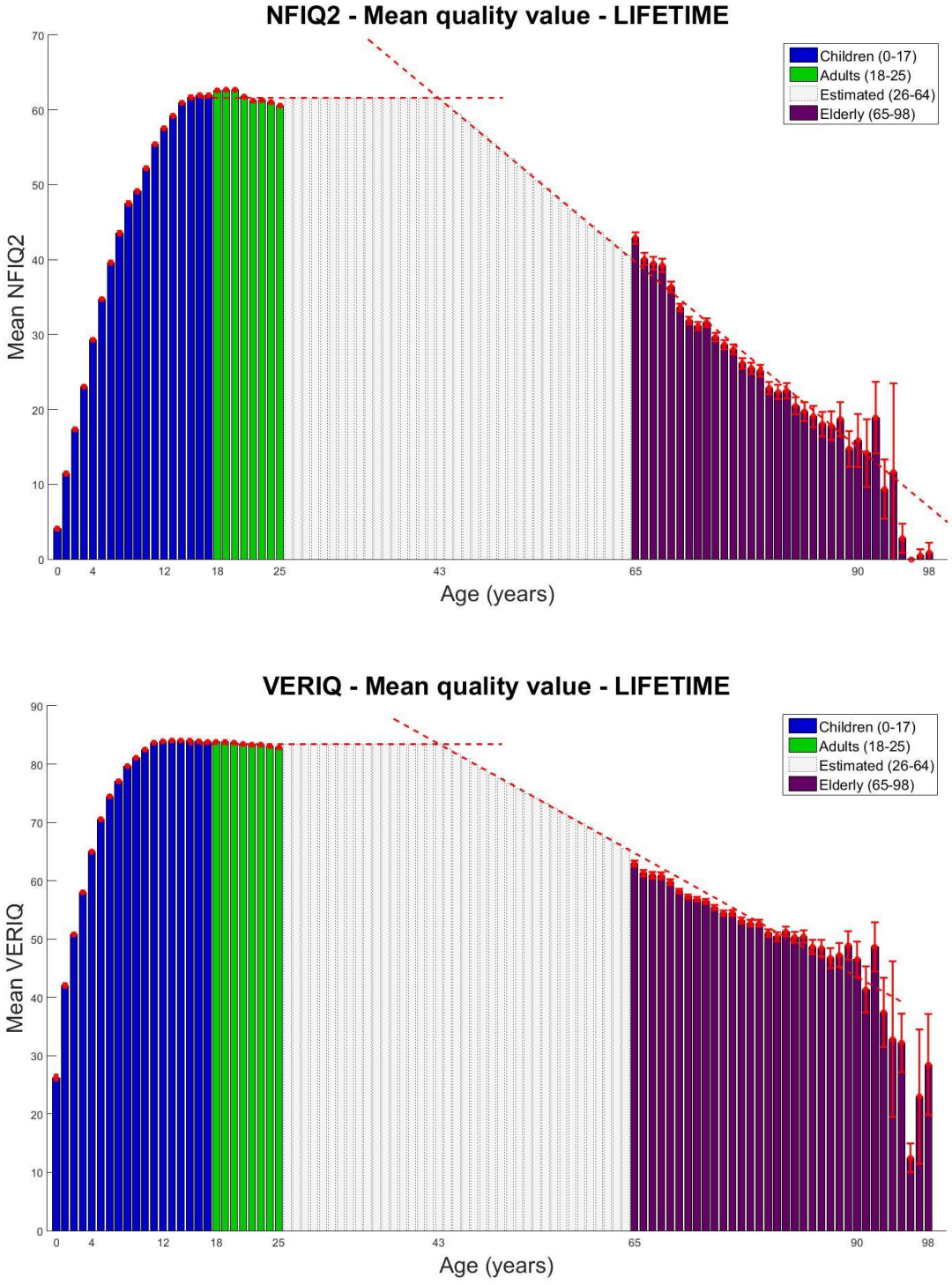

Figure 17 Lifetime mean quality value of fingerprints according to NFIQ2 (top) and VERIQ (bottom). Real values computed from the final experimental DATASET are plotted in black (children and elderly) and green (adults). Estimated values are plotted in light red

The age-wise evolution of fingerprint quality shown in Figure 16 allows us to conclude that:

FINDING 2.

Fingerprint quality of children increases between 0 and 12 years of age. This increase is very fast between 0 and 4 years of age while it reduces its rate between 5 and 12. From 12 years old until 17, fingerprint quality becomes stable and can be considered equal to that of adults (18-25).

FINDING 3.

For adults, fingerprint quality is quite stable, with an almost negligible decreasing slope between 18 and 25 years. Given the limited amount of data available for adults from an age-wise perspective, covering only ages 18-25, this invariable behaviour of fingerprint quality for adults should still be further confirmed.

FINDING 4.

For elderly in the range 65-90, fingerprint quality decreases linearly with age. According to the estimation made in the study, this linear decrease starts at around 40-45 years of age.

It is interesting to underline that for 65-year olds, fingerprint quality is similar to that of 4 years old children.

4.1.2 Age effect: Matching

As mentioned in the description of the experimental protocol in Section. 3.3.1.2, the matching tests were performed to confirm, or to complement if necessary, the observations made in the quality-related results presented in the previous section.

Matching results have been obtained on approximately one fifth of the data of the quality results as explained in the general experimental protocol in Section 3.3: 426,336 fingerprint samples for the quality experiments versus 87,011 fingerprint pairs (i.e., matching scores), for the matching experiments. This means that from a statistical perspective, matching results are slightly less reliable. The figure remains however statistically relevant and offers the possibility to issue solid conclusions.

Figure 18 shows the comparison of the genuine score distributions, both for VeriFinger (top) and NIST/NBIS (bottom), of the three overall age groups in the final experimental DATASET: children, adults and elderly.

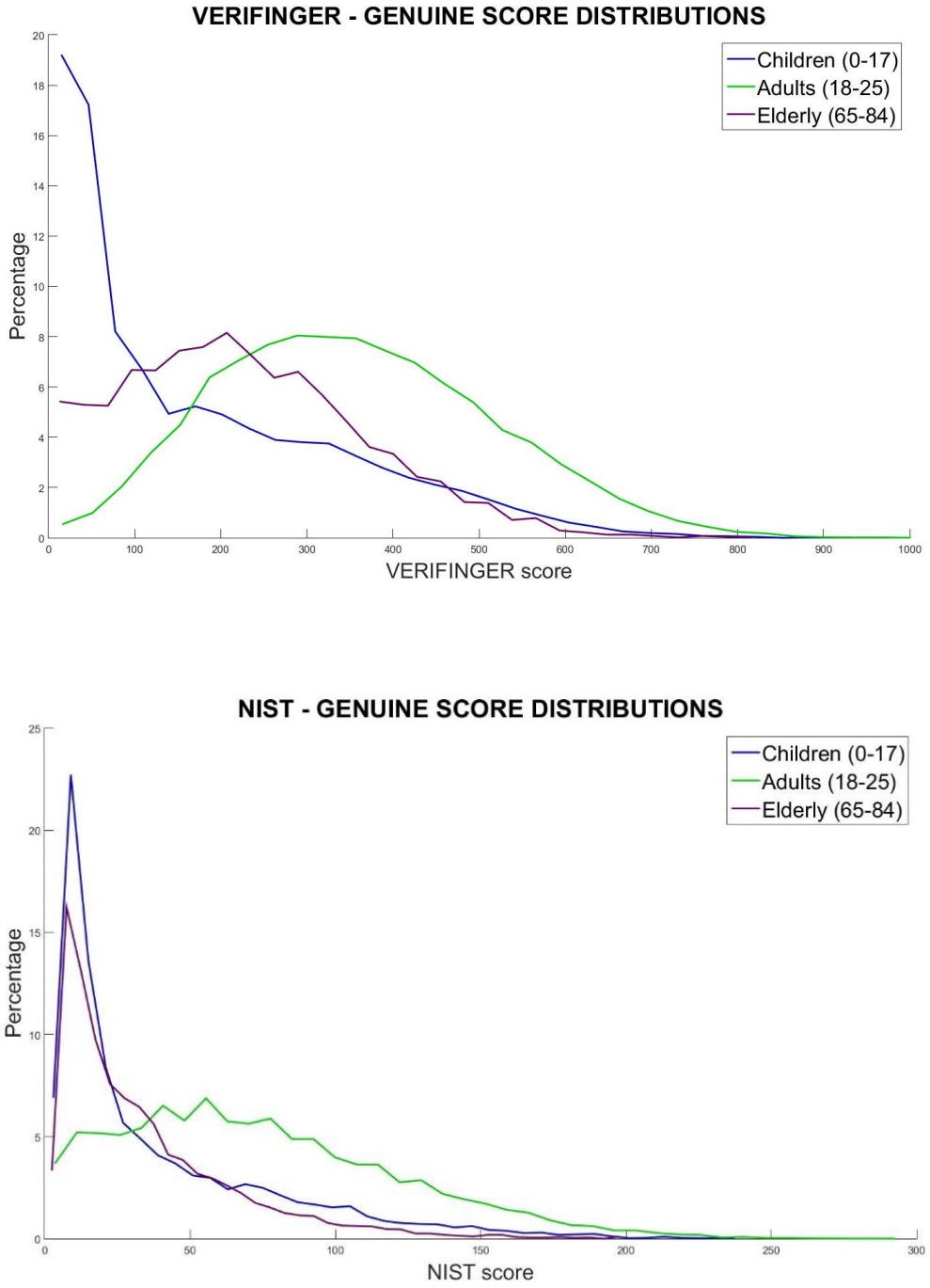

Figure 18 Comparison of the children, adults and elderly genuine score distributions computed with VeriFinger (top) and NIST/NBIS (bottom).

As in the case of quality, given the non-uniformly age distribution of data in the final experimental dataset, the genuine scores distributions shown in Figure 18 should be taken as a general indication of matching performance and not as a perfect representation of reality.

The general trends observed in the case of quality are not exactly reproduced by the genuine score distributions. While children presented a better overall quality than elderly, results presented in Figure 17 show that:

FINDING 5.

Children fingerprints present overall a better quality than elderly fingerprints. This findings is in line with FINDING 1. However, elderly fingerprints still perform better (in the case of VeriFinger) or at least equally well (in the case of NIST/NBIS), than children ones. Better quality in this specific case does not directly translate into better matching performance.

This apparent discrepancy between FINDING 1 (quality) and FINDING 5 (matching) may have two possible explanations derived from the type of data normally used to train and test matchers and quality metrics:

- As explained in Section 3.2.1, the quality metrics used in this study were exclusively trained on adults' data. This is the case for the vast majority of quality metrics proposed in the literature. As such, the discrepancy pointed out above could be explained by the fact that quality metrics designed for adults may be inaccurate when predicting the performance of children data. Considering the age range of the adults' fingerprints used for their training, this lack of reliability could also be applicable to elderly fingerprints (e.g., if training data does not take into consideration fingerprints above 50 years of age). To confirm this hypothesis, specific quality metrics should be developed for children and elderly and compare their results to those of standard adult metrics.
- Similarly, as for quality metrics, fingerprint matchers are typically trained and tested on adults' data. This means that they are adapted to the size of adult fingerprints. As such, they may be unable to extract all the discriminative potential of children's fingerprints even if these are of a good-enough quality. To confirm this hypothesis, it would be necessary to develop and evaluate matching algorithms specifically designed to work with children fingerprints.

For further details that confirm the conclusion stated above, the reader is invited to review Annex 3 for the genuine score distributions of the different subgroups considered within the children and elderly groups: children1 (0-4), children2 (5-12), children3 (13-17), elderly1 (65-69), elderly2 (70-74), elderly3 (75-79) and elderly4 (80-85).

Following the quality experiments, Figure 19 shows the year-by-year evolution of the mean genuine matching score value. The 90% confidence intervals for each of the mean values are shown as vertical red lines. As can be observed, for several of the mean genuine matching score values the 90% confidence intervals are quite large which indicates that results should be taken with care. Even if these values are not fully reliable, they do help to show the overall trends of fingerprint matching score with respect to age.

For the ages not present in the final experimental dataset, ages between 26 and 64 (plotted in light grey in Figure 19), the mean genuine scores have been estimated using values corresponding to ages 18-25 (plotted in green) and 65-84 (plotted in purple). The estimation process has been the same as in the case of quality.

Mean genuine scores corresponding to ages 85-98 have been excluded from the estimation process due to the lack of matching finger-pairs.

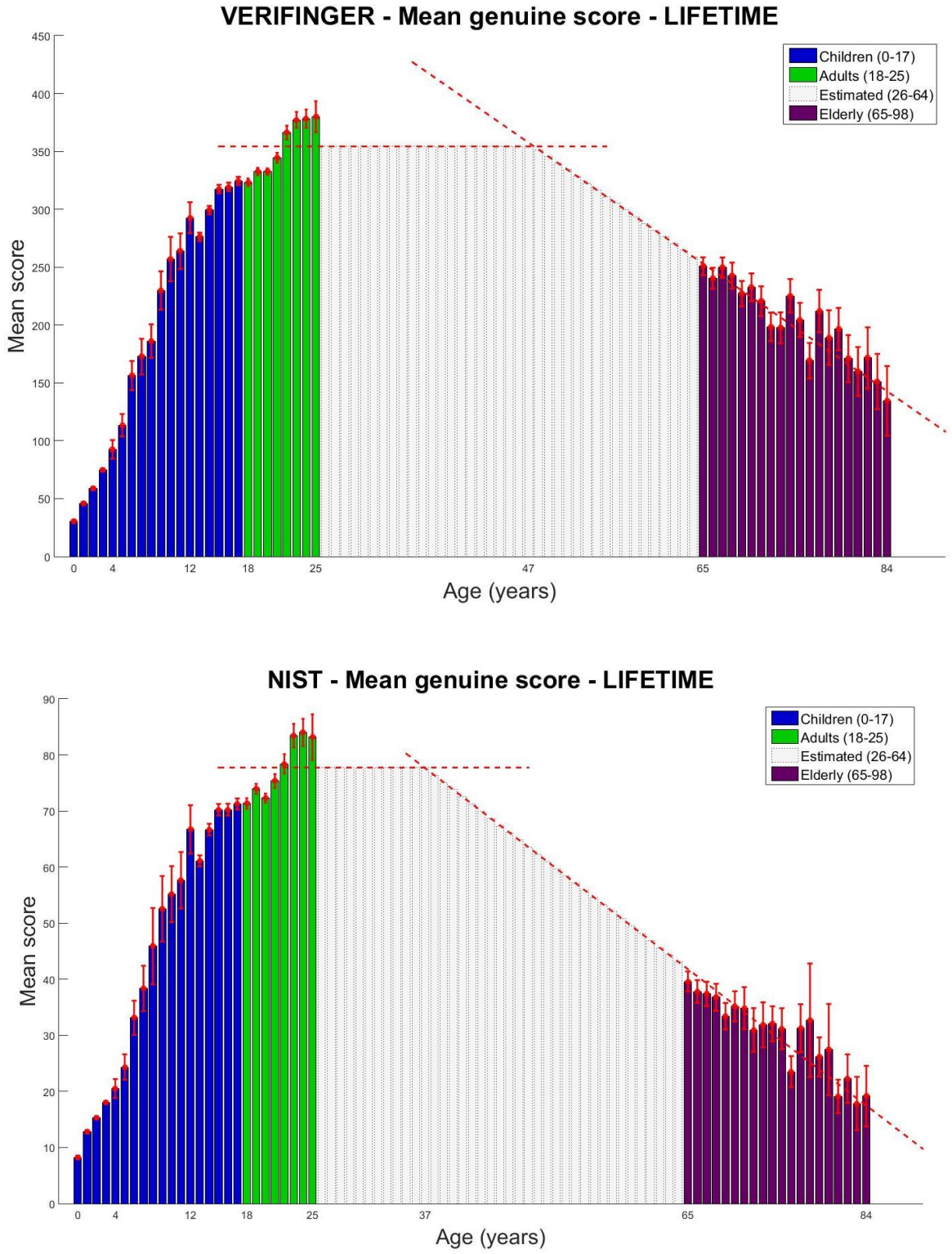

Figure 19 Lifetime mean genuine score value according to VERIFINGER (top) and NIST (bottom) matchers. Real values computed from the final experimental DATASET are plotted in black (children and elderly) and green (adults). Estimated values are plotted in light red (26-65)

The matching results shown in Figure 19 are consistent with the equivalent quality-related results presented in Figure 18. The conclusions drawn from the quality experiments are confirmed with the following small variations:

FINDING 6.

Genuine matching scores of children increase between 0 and 18 years of age. This increase is linear and very rapid between 0 and 12 years of age, while it considerably reduces its rate between 12 and 17.

FINDING 7.

For adults, fingerprint matching score is quite stable. Although a mild increasing trend can be observed between 18 and 25 years of age, given the 90% confidence intervals, it is not possible to ascertain such improvement.

As in the case of quality, given the limited amount of data available for adults from an age-wise perspective, covering only ages 18-25, stable behaviour of fingerprint genuine matching performance for adults should still be confirmed.

FINDING 8.

For elderly in the range 65-84, fingerprint genuine scores decrease linearly with age. According to the estimation made in the study, this linear decrease starts between 37 and 47 years of age.

The mean value of genuine scores of 65-year olds, is equivalent to those of children between 8 and 11 years old.

4.1.3 Conclusions of the age-effect experiments

CONCLUSION 1.

From a quality point of view, children fingerprints show better quality than those of elderly. However, from a matching perspective, elderly fingerprints result in either as good as or even higher matching scores than children fingerprints ones. Both from a quality and a matching perspective, adult's fingerprints are clearly those that present the highest matching score.

CONCLUSION 2.

Fingerprints quality and genuine matching scores increase very rapidly between 0 and 12-15 years of age, and then they become stable. Assuming that the extrapolations proposed are confirmed latter, both seem to remain fairly constant during adulthood until 40-45 years of age. At 40-45, both start decreasing linearly.

The results presented in this section have demonstrated the great challenge posed by very young children (0-4) and by the elderly (especially above 70-years of age) to fingerprint recognition systems. Based on the results obtained and on previous experience, we present here probable explanations for this poor performance and we put forward two hypotheses on how to improve the interaction of these challenging age-groups with fingerprint-based technology.

The size of the fingerprint and the frequency (width) of ridges and valleys are two parameters that are taken into account in the development of quality metrics and feature extractors/matchers. These parameters are typically adapted to the average size and ridge width of adult fingerprints. As such, the small overall size and narrow ridges structure of fingerprints belonging to very young children (0-4 years of age) is likely to contribute to their low quality and poor matching score.

HYPOTHESIS 1.

Developing specific quality metrics and matchers adapted to the reduced-size of children fingerprints could significantly improve simultaneously both their quality score and their genuine matching scores.

For the elderly, as for adults, the fingerprints size and ridge width remain basically invariable. However, the skin condition changes, gradually losing its elasticity and becoming drier [14]. These variations hinder the acquisition with current live-scan touch-based scanners, which entails a decrease in their overall quality.

HYPOTHESIS 2.

New touchless technology could improve the quality and matching scores of elderly fingerprints. With current touch-based technology, moisturizing the fingertip skin prior to the acquisition could potentially help to obtain images with better quality.

4.2 Ageing effect

The results presented in this section have been obtained following the experimental protocol described in Section. 3.3.2 (see Figure 11).

4.2.1 Children case

Figure 20 and Figure 21 show, for the VeriFinger and NIST/NBIS matchers respectively, the evolution of the mean genuine scores when the time difference between the two templates from same data subject increases from 0 to 7 years. Results are given for age group categories: children1 (0-4), children2 (5-12), children3 (13-17) and adults (18-25), this last one is plotted as reference. For each of the figures:

- The top plot shows the mean absolute values of the genuine scores distributions, that is, mean values corresponding to the distributions shown in Figure 20 (VeriFinger) and Figure 21 (NIST/NBIS) in Annex 4. For each point, the 90% confidence interval is given as a vertical bar. In these plots, the lower the curve, the worse the matching score.

- The bottom plot shows the same results, but in this case the mean values have been normalized so, that in all cases the mean genuine score for a time difference of 0-1 years between the fingerprints compared represents 100%. This way it is possible to visualize the variation in percentage of the mean value: the steeper the slope the larger the ageing effect.

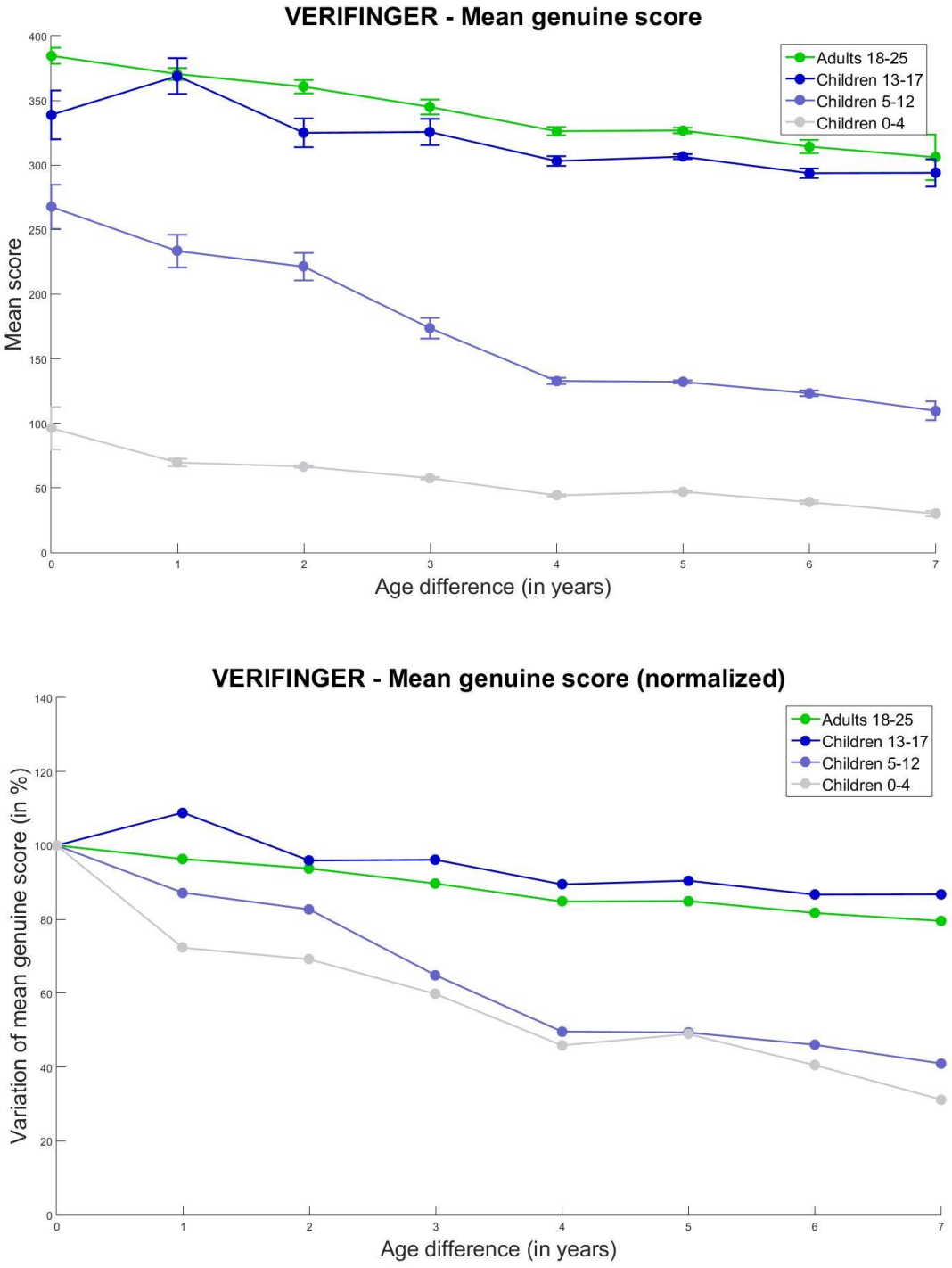

Figure 20 Evolution of the mean genuine score (top) and the normalized mean genuine score (bottom) for an increasing time difference between the enrolled and test sample for age-groups: children1 (0-4), children2 (5-12), children3 (13-17) and adults (18-25). Scores computed with VeriFinger.

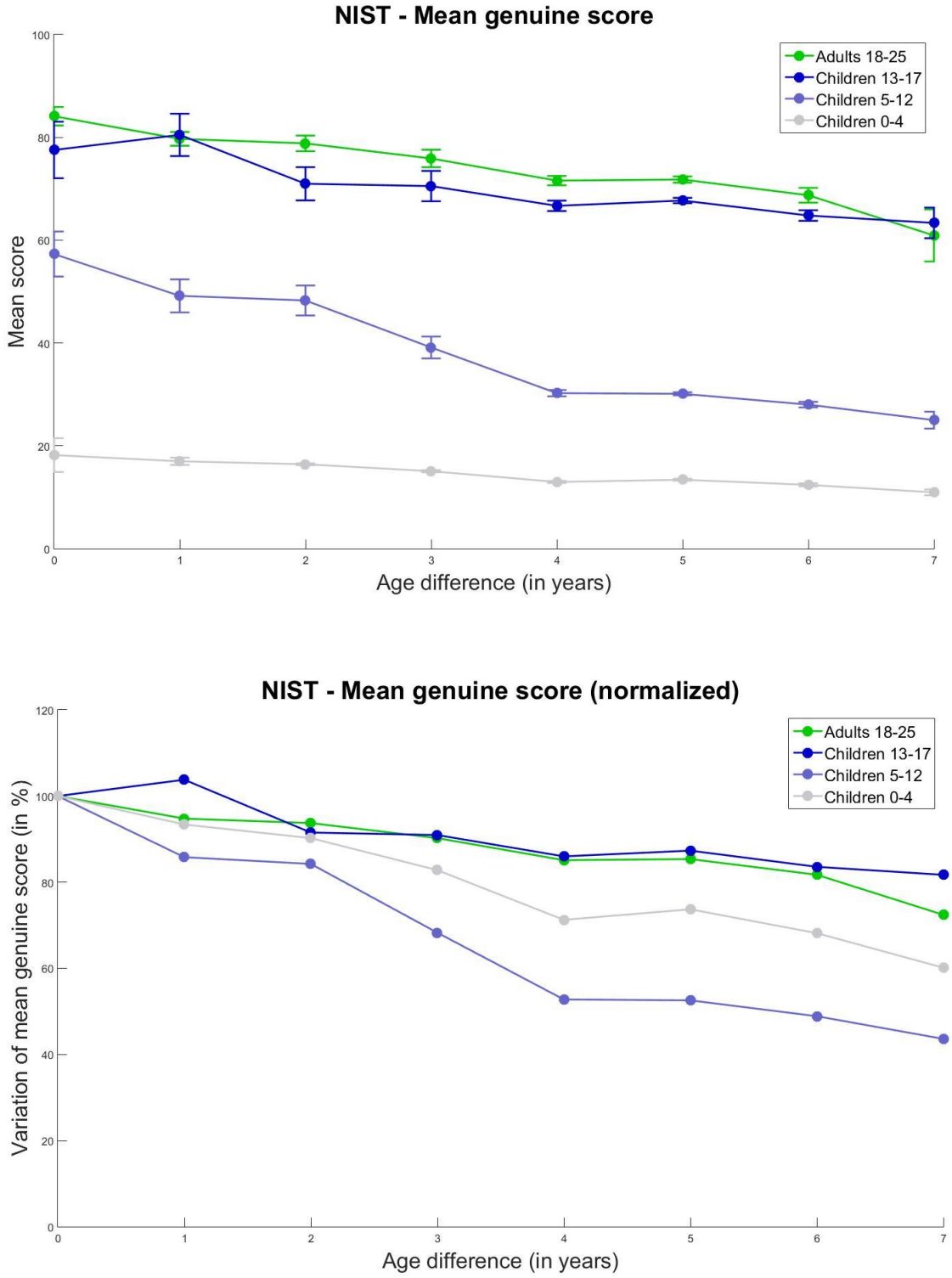

Figure 21 Evolution of the mean genuine score (top) and the normalized mean genuine score (bottom) for an increasing time difference between the enrolled and test sample for age-groups: children1 (0-4), children2 (5-12), children3 (13-17) and adults (18-25). Scores computed with NIST/NBIS

Figure 20 and Figure 21 show, that both matching algorithms considered in the experiments, NIST/NBIS and VeriFinger, present a very similar behaviour with respect to the ageing of the enrolled/test samples. The main conclusions that may be extracted from these results are:

FINDING 9.

Looking at the absolute performance, i.e., top plot in each figure, the results obtained in the age-effect experiments presented in Section 4.1 are here as well confirmed: children fingerprints in the range 0-4 present lower level matching score than children fingerprints in the range 5-12, while results for children 13-17 and adults are very similar.

FINDING 10.

For all groups, a larger time difference between the two collected samples implies a loss in matching score. Ageing effect is therefore confirmed.

This decreasing of the matching score after 7 years is:

- Around 10% in the case of adults and children 13-17 year old
- Around 50% in the case of children 5-12 year old and 0-4 year old.

FINDING 11.

For adults and children between the 13-17 years of age, the total 10% of matching score loss is almost linear between 0 and 7-years difference, i.e., there is around a 1.5% loss every 1-year increase between the two collected samples.

For children of age between 0-4 and between 5-12, the loss is not linear and the biggest ageing effect occurs when the time difference between the two collected samples goes from 2 to 4 years (steepest slope in the bottom plot of each figure). In this 2-year time gap there is a 30%-40% matching score loss (out of the total 50% in 7 years).

4.2.2 Elderly case

Figure 23 and Figure 23 show analogue results to those shown for children in Figure 20 and Figure 21, but in this case for the elderly subgroups: elderly1 (65-69), elderly2 (70-74), elderly3 (75-79), elderly4 (80-98) and the reference adults population (18-25). As before, for each of the figures the top plot shows the mean absolute values of the genuine scores (see detailed score distributions in Annex 4), while the bottom plot shows the normalized mean values so that in all cases the mean genuine score for a time difference of 0-1 years represents 100%.

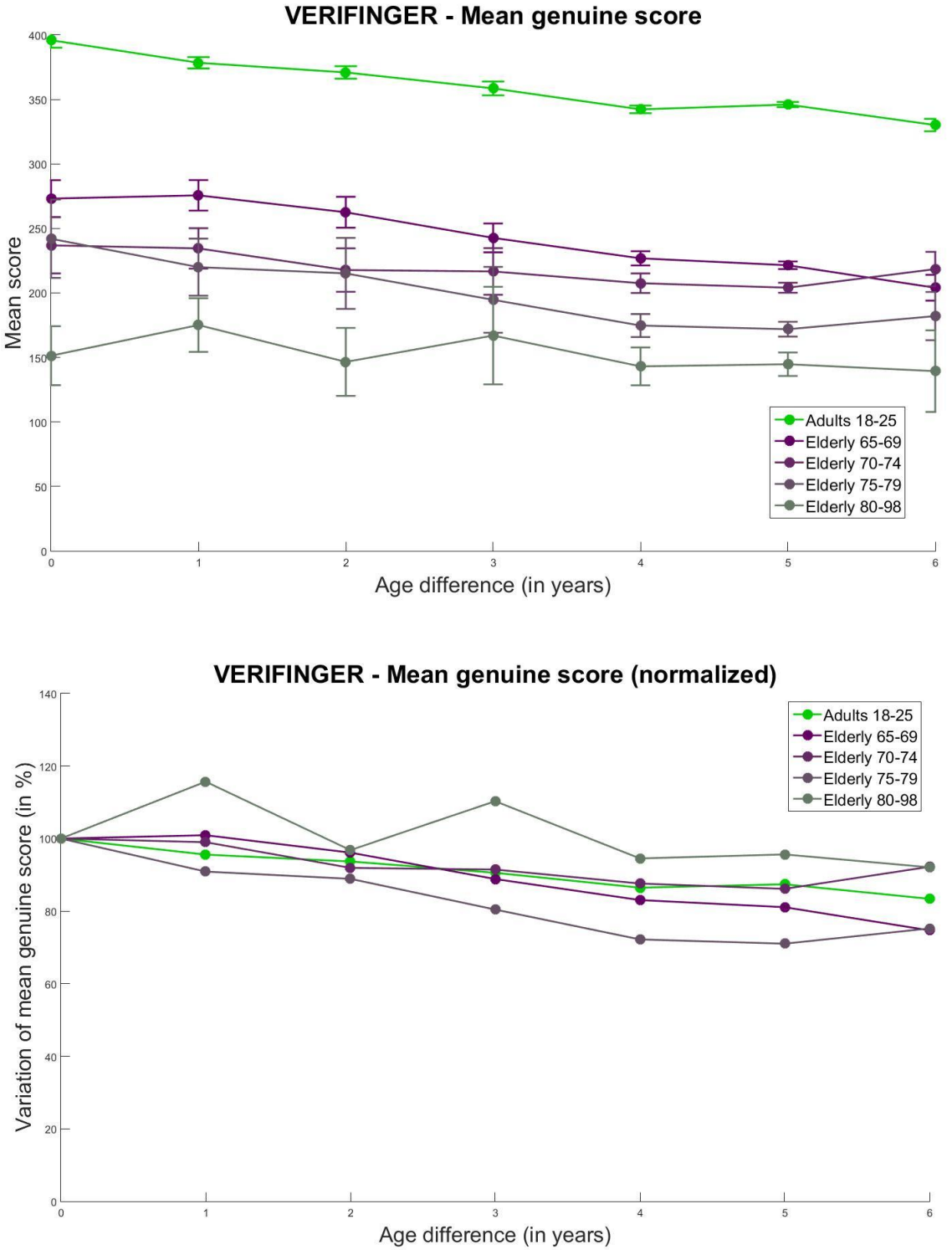

Figure 22 Evolution of the mean genuine score (top) and the normalized mean genuine score (bottom) for an increasing time difference between the enrolled and test sample for age-groups: elderly1 (65-69), elderly2 (70-74), elderly3 (75-79) and elderly4 (80-98) and adults reference population (18-25). Scores computed with VeriFinger.

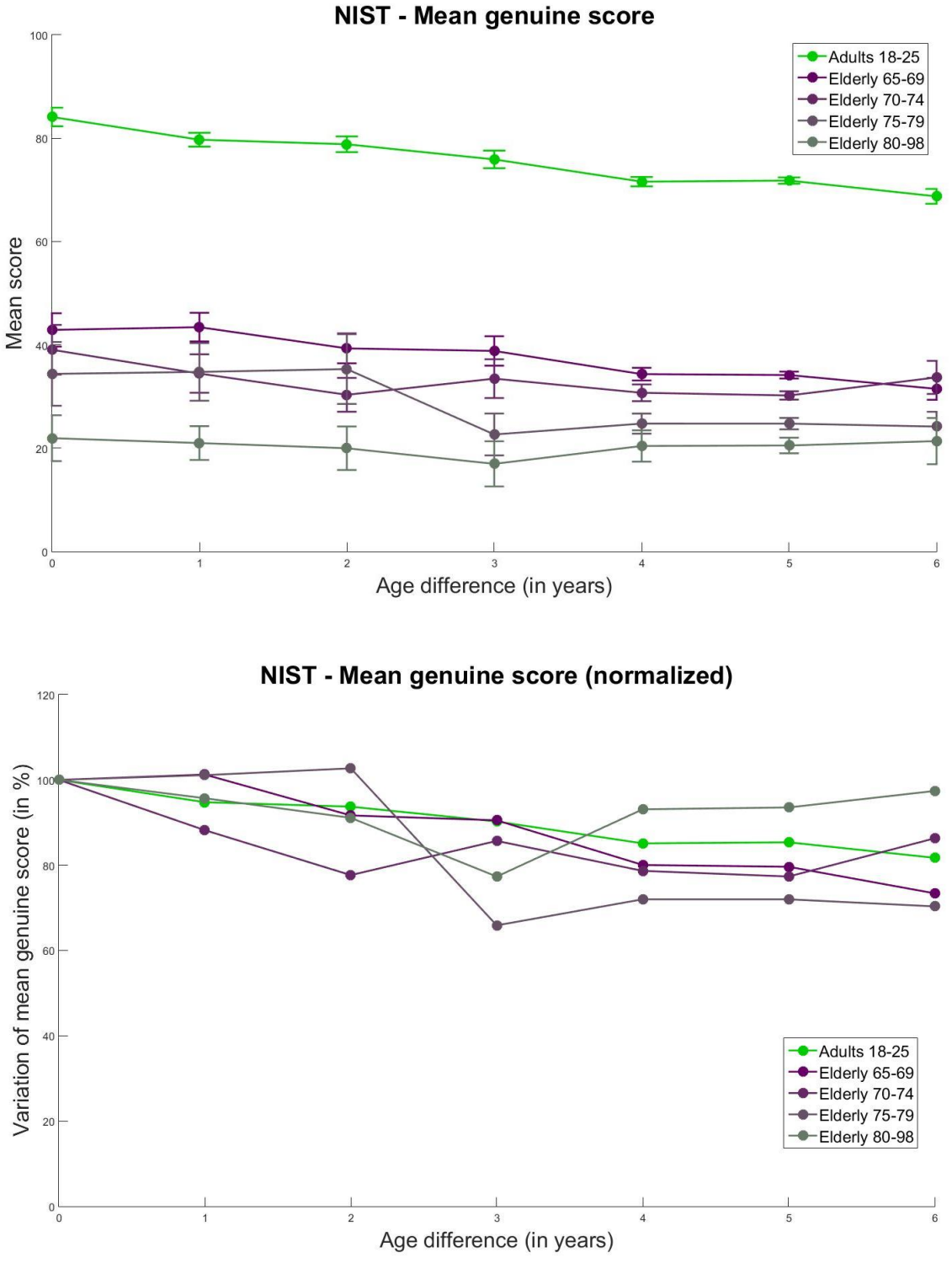

Figure 23 Evolution of the mean genuine score (top) and the normalized mean genuine score (bottom) for an increasing time difference between the enrolled and test sample for age-groups: elderly1 (65-69), elderly2 (70-74), elderly3 (75-79) and elderly4 (80-98) and adults reference population (18-25). Scores computed with NIST/NBIS.

As in the case of children, both matching algorithms show a very similar behaviour with respect to elderly from an ageing perspective. The next set of conclusions may be drawn from the results presented in Figure 23 and Figure 23:

FINDING 12.

Looking at the absolute performance, i.e., top plot in each figure, the results obtained in the age-effect experiments presented in Section 3.3.1 are confirmed: elderly fingerprints present a worse matching score as the age of the template increases, that is, age group 65-69 performs better than 70-74, which performs better than 75-79, which performs better than 80-98.

FINDING 13.

For all groups, a larger time difference between the two collected samples implies a loss in the matching score. Ageing is confirmed. This matching score loss is very similar for all groups: 10%-20%.

FINDING 14.

For all groups, the total 10%-20% of matching score loss is almost linear between 0 and 6-years difference, i.e., there is around a 1.5%-3% loss every 1-year increase between the two samples compared.

4.2.3 Conclusions of the ageing-effect experiments

The conclusions reached above from the ageing experiments presented in Figure 20 and Figure 21 for children and in Figure 23 and Figure 23 for elderly may be summarized as:

CONCLUSION 3.

Ageing effect occurs for all age groups: the larger the time difference between the two collected samples, the larger the matching score loss. This happens for a time difference as small as 1-2 years.

CONCLUSION 4.

Ageing effect is larger for children between 0 and 12 years old. In this age range, for a time difference of 7 years there is a matching score loss of around 50%.

For the categories of 13 and 98 years of age, ageing effect is similar. It occurs linearly with a matching score loss of around 1.5%-3% every increase of 1 year between the two collected samples.

The previous findings have shown that the segment of the population most affected by ageing are children between 0 and 12 years of age. For this range, children grow at a very rapid rate. From our perspective, the displacement of the minutiae points due to the fast growth is the most probable reason for the relatively important ageing effect observed for this age group. Based on this rationale, the following hypothesis can be made:

HYPOTHESIS 3.

From an algorithmic perspective, the development of a reliable growth model for fingerprints between 0 and 12 years could help to predict the new position of minutiae points at a certain point in time in the future with respect to the enrolled template, helping in this way to reduce the ageing effect.

From a pure procedural perspective, ageing can also be mitigated by reducing the validity of the enrolled samples (i.e., in the case of travel documents this would entail a shorter expiry period).

The experiments reported in the following Section 5 of the present report have been designed to confirm/refute this HYPOTHESIS 3.

5 Growth model

The results presented in Section 4.2 have shown that the ageing effect is clearly higher for children between 0 and 12 years of age. For this segment of the population there is a loss of 50% of the genuine matching score with a time lapse of seven years, compared to the 10%-20% decrease observed for the rest of the population (ages 13 to 98).

As already pointed out at the end of Section 4.2.3 the most plausible cause for this higher ageing effect in the case of young children is their rapid growth (and by extension the rapid growth of their fingers), which results in the displacement of the minutiae between a fingerprint enrolled at two different times.

In HYPOTHESIS 3, it was stated that the development of a reliable growth model for fingerprints between 0 and 12 years of age can help to predict the new position of the minutiae points in the future with respect to the enrolled template, thus helping to reduce the ageing effect.

The present section describes the development and validation of a growth model for children fingerprints.

5.1 Development of the growth model

The growth model is defined as a mathematical function $f(P)$ in a following way:

> Given the location of a minutia point $P^{t0}=(x_0,y_0)$ with respect to the center of the fingerprint at an acquisition time t0, the function outputs an estimation (as accurate as possible) of the location of that same minutia point at a different point in time t1, $P^{t1}=(x_1,y_1)$. That is:
>
> $$P^{t1} = f(P^{t0})$$

In the following, the key assumption for the development of the growth model is that (see Figure 24):

> The fingerprint grows from the center outwards. The area of interest for this assumption will be limited to the distal phalanx also called last fingertip. This essentially means that the center of the fingerprint is the "growth origin" and therefore the location of the center of the fingerprint is not affected by the growth (i.e., it is not displaced during to growth). This way, the center of the fingerprint can be taken as a reference (center of origin) at any point in time in order to measure relative distances. That is, the center is located at (0,0) at time t0 and continues to be located at (0,0) at time t1. On the other hand, any minutia point that is at a distance D0 from the center at time t0 will be at a distance D1 from the center at time t1 independently of the position of the fingerprint on the live-scan device (e.g. rotation and translation invariant). The variation between D0 and D1 is assumed to be caused by the growth of the distal phalanx.

With this assumption in mind, the growth model is generated following the protocol described in the next steps.

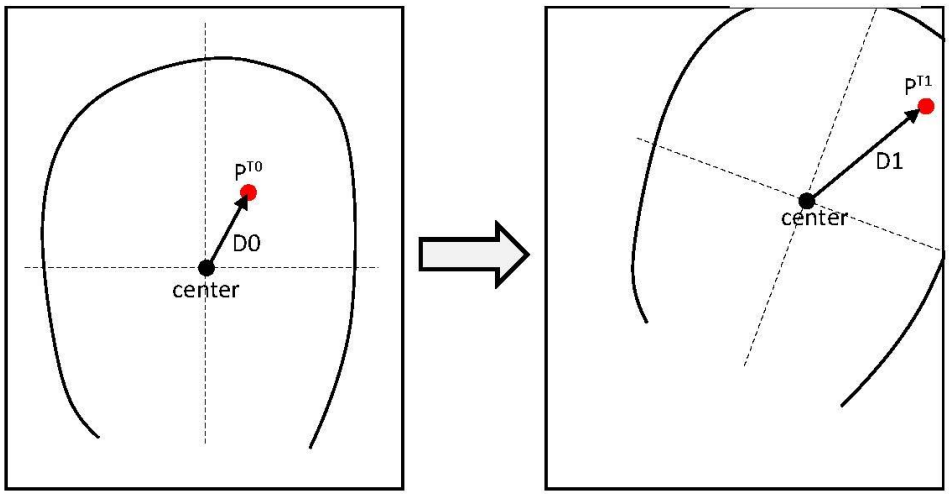

Figure 24 Diagram showing the key steps followed to generate the growth model.

STEP 1. The model development dataset was selected from the experimental dataset. This development set is composed of a total 105 fingerprint pairs.

The first fingerprint of all the pairs was acquired at t0=5 years old. This decision was made with respect to the amount of fingerprint pairs available. As can be seen in Annex 2, the number of fingerprint pairs in the final experimental database whose first fingerprint was acquired at T0=5 is:

	TOTAL NUMBER OF FINGERPRINT PAIRS (FINAL EXPERIMENTAL DB)							
	Time difference between samples (in years)							
	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8
T0=5 years	26	52	56	95	819	3495	765	75

The second fingerprint of the 105 development pairs was acquired at t1=5 years old (15 pairs), t1=6 (15 pairs), t1=7 (15 pairs), t1=8 (15 pairs), t1=9 (15 pairs), t1=10 (15 pairs), t1=11 (15 pairs).

Put in another way, the development set contains 7×15 pairs of fingerprints. For each of the seven groups (of 15 pairs), the time difference between the enrolled fingerprint (t0) and the test fingerprint (t1) is: 0 years, 1 year, 2 years, 3 years, 4 years, 5 years and 6 years.

The main criteria for the selection of the pairs was the maximization of the average quality of the two fingerprints. That is, for each of the 7 sub-groups, the 15 pairs with the highest average quality in the experimental database were selected.

STEP 2. For each of 105 development pairs, three examiners (35 pairs each) manually marked:

1. The center of the fingerprint (from which the fingerprint grows). Given that all relative distances are measured with respect to this center, it is critical that *the exact same point* is selected as center of the fingerprint in both samples.
2. 12 minutiae points in the first fingerprint of the pair (acquired at t0=5 years old), and *the corresponding 12 minutiae points* in the second fingerprint of the pair (acquired at t1=6-11 years old).

For the marking process, a specific software tool was developed that allows the examiner to: 1) visualize both fingerprints of the pair simultaneously, 2) mark the center of the fingerprint and 3) mark which are the 12 corresponding minutiae points between the T0 fingerprint and the T1 fingerprint.

For the selection of the 12 minutiae points, two main guidelines were followed:

1. Preference was given to those minutiae located in the periphery. Different works [12], [13] have shown that this is the part of the fingerprint where the least amount of elastic distortion may be found (due to the touch-based acquisition technology used).
2. Minutiae were selected covering the largest area possible around the center to ensure an even coverage of all directions.

As a result of this step, for each of the 7 subgroups of 15 fingerprints, there are a total 15×12=180 corresponding coordinates of minutiae points located with respect to the center of the fingerprint for both t0 and t1.

STEP 3. For each of the 7 subgroups of 15 fingerprints, the Euclidean distance of the 180 minutiae points is calculated with respect to the center at t0 and t1, resulting in distances D0 and D1 (please see Figure 24).

The 180 pairs (D0, D1) are represented in the 7 plots (one plot for each age difference) shown in Figure 25.

In these plots the dashed diagonal line represents the equidistant case D1=D0, that is:

- A point on this line implies that the corresponding minutiae point has not been displaced between t0 and t1 or, put in other words, there has been no growth.
- A point below this line implies that D0>D1, which means that the corresponding minutia point has got closer to the center (effect opposite to growth).
- A point above this line implies that D1>D0, which means that the corresponding minutia point has moved away from the center (growth).

Ideally, there should be no points below the dashed D1=D0 line as, for children, fingerprints should grow and not diminish in size. However, the location of the minutiae points is not perfect as it is affected by "spatial noise" mainly originating from: 1) the elastic distortion of the skin due to the touch-based technology used to acquire the fingerprints; 2) human errors in the marking of the minutiae points.

Since the growing effect is expected to be relatively small, in some specific cases, the "noise" affecting the location of the minutiae can exceed the growth factor. As a result, some points in Figure 25 are placed below the D1=D0 line. However, from a statistical perspective, taking into account all 180 points, the growth factor should be visible (as will be shown in the next steps of the protocol).

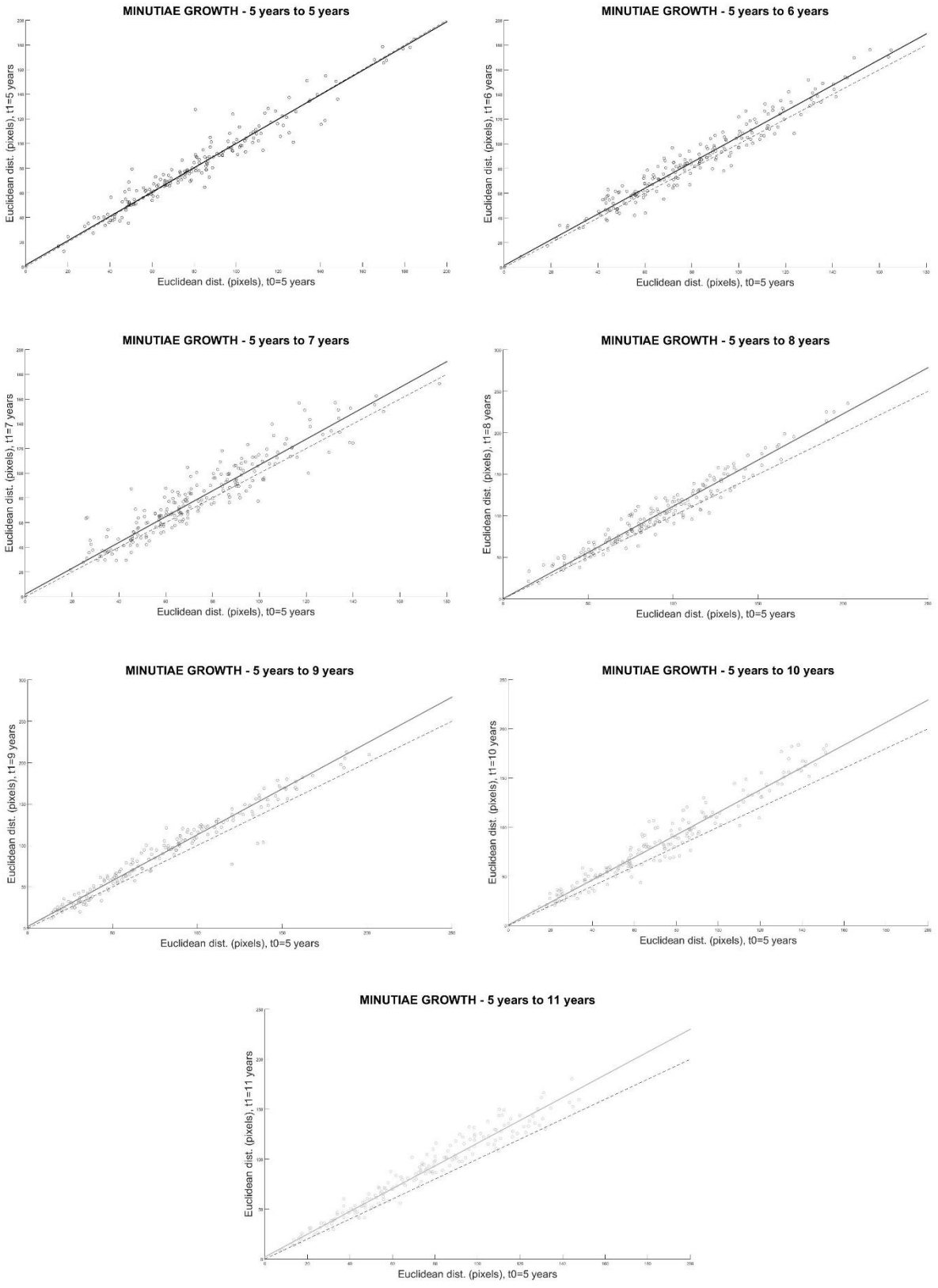

Figure 25 For each plot every point represents the Euclidean distance D0 of a minutiae point from the center of the fingerprint measured at t0, with respect to the Euclidean distance D1 of the same minutiae point measured at t1. The dashed diagonal line represents D0=D1. The solid line represents the best Least Squares linear fit for all the points in the plot.

STEP 4. As can be seen, in all 7 plots, the 180 points representing a pair (D0, D1) are arranged following a straight line. This observation has a very important implication:

CONCLUSION 5.

The growth factor is independent of:

1) the distance of the minutiae to the center of the fingerprint and

2) the placement of the minutiae with respect to the center.

Essentially this means that the fingertip grows from the center outwards, at the same rate, in all directions. Therefore, the isotropic growth of fingerprints is confirmed.

The confirmation of the fingerprints isotropic growth entails that the growth model function, which was the objective of this development phase, can be defined as follows:

$$P^{t1} = gf \cdot P^{t0}$$

Where *gf* is the constant growth factor for a specific pair of points in time (t0, t1). That is, the position of the minutiae point *P* at time t1 can be estimated by multiplying the position of the minutiae point *P* at time t0 by a specific growth factor *gf*.

The next steps of the development phase are focused on defining how to compute the growth factor *gf* for any given pair (t0, t1).

STEP 5. For each of the 7 cases shown in Figure 25, the best linear fit for all the points is computed using Least Squares. The result of this process are the solid lines shown in each of the plots (Figure 25).

The constant growth factor for each age pair (t0=5, t1=[5-11]) is defined by the gradient of the line. The steeper the line, the larger the growth factor.

In order to have a better visual comparison of the growth factor for each age difference considered, all 7 linear fits are shown together in Figure 26. In this figure we can already observe that the growth factor follows a logical evolution:

- For 0 years difference the growth line almost perfectly coincides with D1=D0, which, as explained above, implies that there has been no growth, i.e., *gf*=1.
- The rest of the lines are all above the D1=D0 line which implies a growing effect.
- Lines for age differences 1-6 gradually get steeper, that is, the larger the time difference between fingerprints, the larger the growing effect.

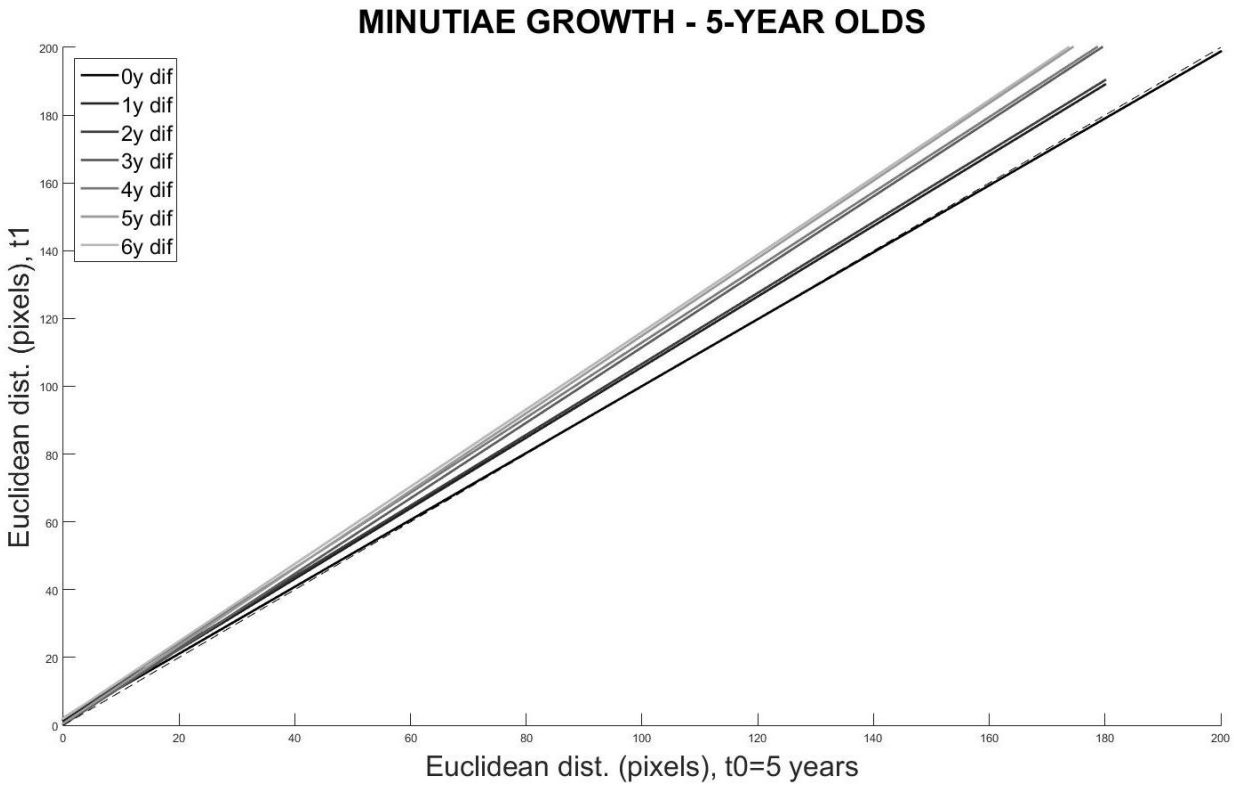

Figure 26 Linear fits from Figure 24 representing the growth factor (gradient of the line) for each age difference between t0=5 years and t1=[5-11] years.

***STEP 6**.*

Table 5 shows the numerical growth factor (i.e., gradient of the lines shown in Figure 26) for the 7 time differences with respect to t0=5 years.

	GROWTH FACTOR (T0=5 years)						
	Time difference between samples (in years)						
	0	1	2	3	4	5	6
GF	0.99	1.04	1.05	1.11	1.12	1.14	1.14

Table 5 Numerical growth factor for t0=5 and t1=[5-11]. These values are the slope of the lines shown in Figure 26.

The growth factor values shown in Table 5 are depicted with respect to age in Figure 27, in blue. The vertical blue lines show the 90% confidence intervals of these values.

The red solid line shows the best quadratic fit for those values, computed using Least Squares. This function is defined as:

$$gf^{t0=5}(t1) = -0.0034t1^2 + 0.08t1 + 0.67 \text{ for } t1 \in [5,11]$$

This function allows computing for children t0=5 years old the growth factor until they will be t1=11 years old.

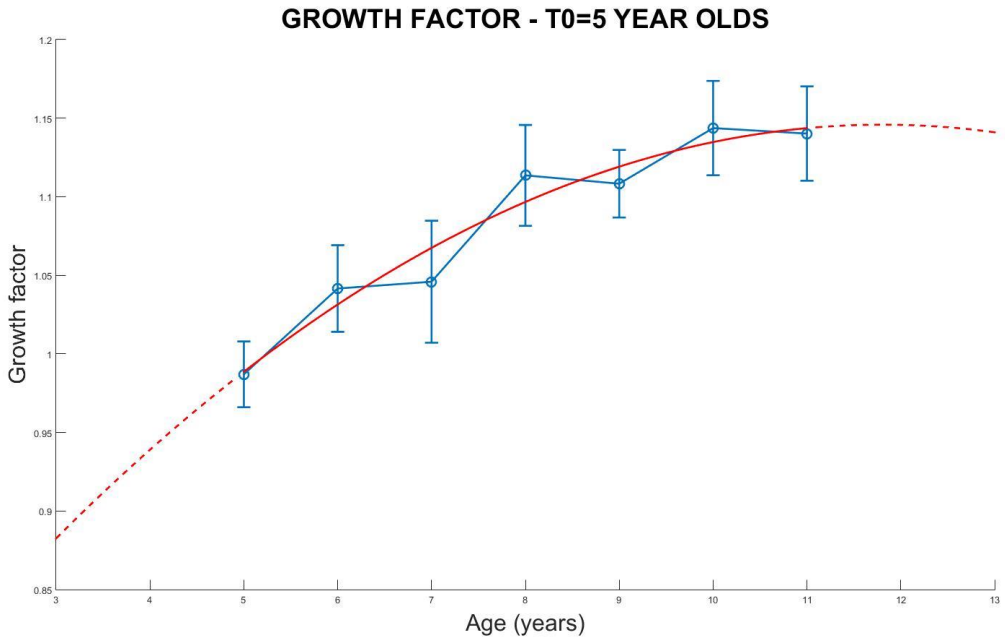

Figure 27 In blue, growth factor values for t0=5 and t1=[5-11] calculated from the real data. Vertical lines indicate 90% confidence intervals. In solid red, the quadratic Least Squares fit for those points.

To sum up, the growth model for 5-year olds can be defined as:

$$f(P^5) = P^{t1} = gf^5(T1) \cdot P^5$$

In general, the growth factor model for any given pair of points in time (T0,T1) would be:

$$P^{t1} = f(P^{t0}, t1) = gf^{t0}(t1) \cdot P^{t0},$$

where $gf^{t0}(t1)$ would have to be processed for each particular t0 following an analogue protocol as the one defined above.

In order to define the growth model for children of ages different from t0=5, an analogue process to the one described in this section should be followed.

Note that the previous growth model works both ways, that is, it can be used to:

- Artificially "grow" a fingerprint captured at t0 in order to estimate what it will look like at t1. This artificially grown fingerprint will be called T0'.
- Artificially "rejuvenate" a fingerprint captured at t1 in order to estimate what it looked like at t0. This artificially rejuvenated fingerprint will be called T1'. This rejuvenating process can be done by simply applying to T1 a "rejuvenating" factor of: $1/gf$.

5.2 Validation of the Growth model

The objective of the validation experiments is to determine, if the use of the growth model developed in the previous section can help to mitigate the significant ageing effect observed in children between 0 and 12 years of age.

For this purpose, a subset of 908 fingerprint pairs has been selected from the final experimental dataset. In all cases, the first sample of the pair was acquired at t0=5 years of age. The second sample of the pair was acquired between ages t1=6 and t1=11 (age difference 1-6 years). The number of fingerprint pairs selected depending on the age difference between the two samples is as follows:

	NUMBER OF FINGERPRINT PAIRS (VALIDATION DB)					
	Time difference between samples (in years)					
	1	2	3	4	5	6
t0=5 years	37	41	80	250	250	250

Some groups present a fewer number of samples as there was not enough data in the experimental dataset in order to reach 250 fingerprint pairs in all cases (see Annex 2 for the total number of fingerprint pairs present in the experimental dataset). None of these pairs were used in the development process.

The validation process of the growth model applied on this subset of data is as follows:

STEP 1. For each of the fingerprints in the validation dataset, the minutiae points were detected using the NIST feature extractor and the respective templates were created (see Section 3.3.3 for further details on this application).

STEP 2. The center of the fingerprint (origin of the growth effect) was manually marked in the first fingerprint of each pair.

STEP 3. For each fingerprint pair, the template corresponding to the first sample (acquired at t0=5) was used as input to the growth model developed in the previous section.

For each sample at t0 a new template was artificially generated with the estimated position of each minutiae point in the template at time T1 with respect to the fingerprint center manually marked in STEP 2. This "artificially grown" minutiae template will be referred to as T0'.

As such, after this process the original 908 fingerprint image pairs (T0,T1) are converted into 908 fingerprint template triplets (T0,T0',T1).

STEP 4. Using the fingerprint template triplets obtained in the previous step, two sets of genuine scores are computed using the NIST matcher for each of the 6 fingerprint sub-groups (depending on the time difference between T0 and T1):

- Genuine score set 1: Original. For each fingerprint triplet, the original template acquired at t0 is matched against the original template acquired at t1. This represents the standard ageing situation.
- Genuine score set 2: Grown. For each fingerprint triplet, the artificially grown template represented by T0' is matched against the original template T1. This represents the situation where the growth model has been used to minimize the ageing effect by "growing" the original template T0.

STEP 5. For each of the 6 data sub-groups (age difference between T0 and T1 is 1-6 years), the average value of the previous two sets of scores is compared. If the growth model is effective, the average value of the "grown" genuine scores should be higher than that of the "original" scores. A diagram showing a summary of the previous 5 steps of the validation protocol is shown in Figure 28.

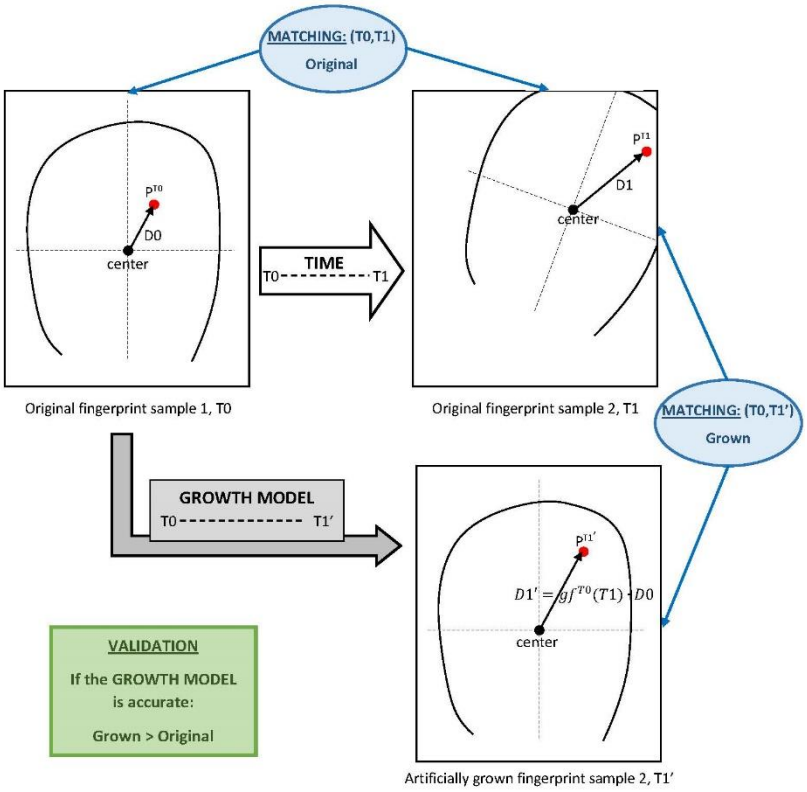

Figure 28 Diagram summarizing the validation protocol of the growth model.

STEP 6. The previous steps 2-5 are repeated but in this case using T1 as the input template to the growth model. Therefore, after manually marking the growth center of the T1 fingerprint the growth model is used to "rejuvenate" the fingerprint and generate an artificial T1' template. Then, the two sets of scores generated are:

- Genuine score set 1: Original. Same as before.
- Genuine score set 3: Rejuvenated. For each fingerprint triplet, the artificially rejuvenated template represented by T1' is matched against the original template acquired at T0. This represents the situation where the growth model has been used to minimize the ageing effect by "rejuvenating" the original template at T1.

Therefore, at the end of the validation process, three different sets of scores are available for each of the 6 fingerprint sub-sets in the validation dataset: 1) original set, 2) grown set and 3) rejuvenated set. The evolution of the average value of this 3 sets of matching scores, depending on the time difference between T0 and T1 is presented in Figure 29. The top chart shows the absolute mean score while the bottom chart shows the normalized score so that the average score for 1-year difference represents 100%.

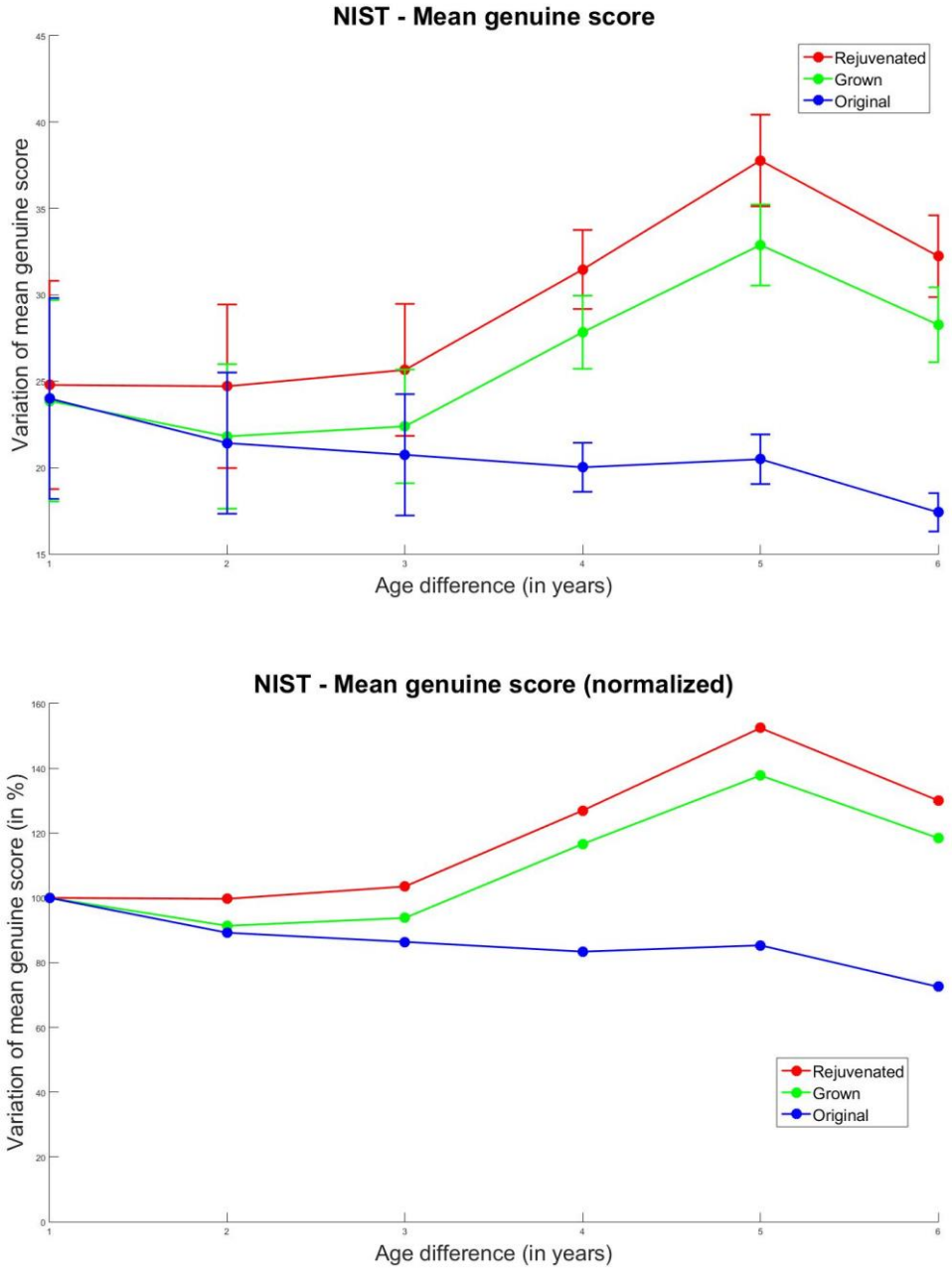

Figure 29 Variation of the average genuine score for the validation experiments of the growth model. The top chart shows absolute mean genuine score values, while the bottom chart shows the normalized mean scores so that the value for an age difference of 1 year represents 100%.

As can be seen in Figure 29, the use of the growth model clearly reduces the ageing effect of the original scores. For a difference between T0 and T1 of 5-6 years there is a relative improvement of around 60%-70% between the original matching scores and those generated after applying the growth model.

"Rejuvenating" (reducing the size of) the fingerprint acquired at t1 results in higher improvement in the matching scores than "growing" the fingerprint acquired at t0. This improvement in performance is likely due to the fact that, on average, the quality of fingerprints acquired at t1 is better than that of fingerprints acquired at t0 (please see the

results on the age-effect presented in Section 4.1). This improvement in quality means that:

- The minutiae points extracted from T1 are more reliable.
- The manual selection of the growth center from T1 is more precise.

These two factors combined account for the 10%-20% improvement of the "rejuvenated" matching scores with respect to the "grown" matching scores.

CONCLUSION 6.

Experiments have shown that using an isotropic growth model will significantly reduce the ageing effect observed in children fingerprints. This result confirms the HYPOTHESIS 3 made in the present report.

6 Conclusions

The research actions conducted on the data have led to 14 findings which have been summarized in the six following conclusions.

CONCLUSION 1.

From a quality point of view, children fingerprints show better quality than those of elderly. However, from a matching perspective, elderly fingerprints result in either as good as or even higher matching scores than children fingerprints ones. Both from a quality and a matching perspective, adult's fingerprints are clearly those that present the highest matching score.

CONCLUSION 2.

Fingerprints quality and genuine matching scores increase very rapidly between 0 and 12-15 years of age, and then they become stable. Assuming that the extrapolations proposed are confirmed latter, both seem to remain fairly constant during adulthood until 40-45 years of age. At 40-45, both start decreasing linearly.

CONCLUSION 3.

Ageing effect occurs for all age groups: the larger the time difference between the two collected samples, the larger the matching score loss. This happens for a time difference as small as 1-2 years.

CONCLUSION 4.

Ageing effect is larger for children between 0 and 12 years old. In this age range, for a time difference of 7 years there is a matching score loss of around 50%.

For the categories of 13 and 98 years of age, ageing effect is similar. It occurs linearly with a matching score loss of around 1.5%-3% every increase of 1 year between the two collected samples.

CONCLUSION 5.

The growth factor is independent of:

1) the distance of the minutiae to the center of the fingerprint and

2) the placement of the minutiae with respect to the center.

Essentially this means that the fingertip grows from the center outwards, at the same rate, in all directions. Therefore, the isotropic growth of fingerprints is confirmed.

CONCLUSION 6.

Experiments have shown that using an isotropic growth model will significantly reduce the ageing effect observed in children fingerprints. This result confirms the HYPOTHESIS 3 made in the present report.

These conclusions allowed the identification of four different age zones for fingerprints, depending on the level of the age effect (i.e., quality/genuine matching score level) and the ageing effect rate. This four age zones are depicted in Figure 30.

The results have also led us to put forward a number of hypotheses (highlighted throughout the text), which give probable explanations to the effects observed in each of the four age zones, and aim at proposing possible solutions to mitigate these effects. These hypotheses need to be further confirmed/refuted through additional development and experimentation, opening this way paths for future research.

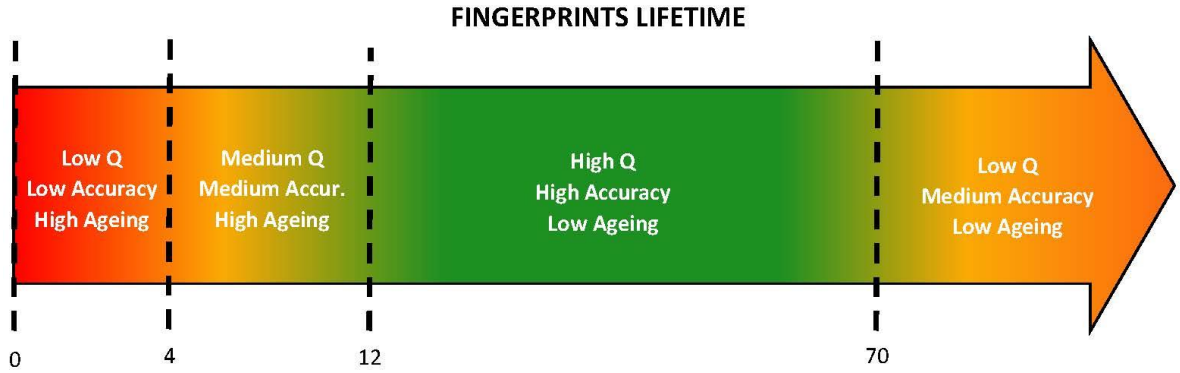

Figure 30 Diagram showing the different age zones in which the fingerprints lifetime can be divided according to their quality/matching and the ageing effect.

The four fingerprint age zones that can be identified thanks to the conclusions of the work are:

- **Very young children, aged 0-4**. This age-group is characterized by poor fingerprint quality and low genuine matching score as well as by a significant ageing effect. Specific algorithms/procedures could be conceived to improve the performance of fingerprint technology working with this segment of the population.

  As expressed in HYPOTHESIS 1, new quality and feature extraction algorithms may be developed, specifically adapted to the small size of these fingerprints and to their narrow ridges and valleys.

  Following the results in the growth-related experiments, it has been shown that the development of a reliable growth model for coping with the displacement of minutiae points through childhood is an efficient tool to mitigate the effect of ageing.

  From a procedural perspective, shorter validity periods for the enrolled samples could also be an advisable measure to put in place for this age group (i.e., apply a more frequent update collection of sample strategy).

- **Children, aged 5-12**. While quality and genuine matching score levels approximate that of adults, the ageing effect is still significantly higher. Therefore, analogue measures to those described in HYPOTHESIS 3 for very young children (0-4) could be followed to mitigate this effect.

- **Teenagers, adults and young-elders, aged 12-69**. For this population segment it can be safely stated that fingerprint recognition systems work as evaluated on adults. Therefore, the use of quality metrics and matching algorithms trained on the adults will be enough appropriate.

- **Elders, aged above 70**. The quality degradation of the fingerprints for this part of the population is quite significant. As stated in HYPOTHESIS 2, the use of touchless or sub-surface acquisition technology could help to improve the performance of fingerprint recognition for this age group. Their accuracy is comparable to that of children aged 5-12 while they present low ageing (similar to that of adults).

  From a procedural perspective, practical enrolment measures such as moisturizing the skin prior to the scanning or using touchless sensors could also help to obtain better quality fingerprints for this age group.

7 Next steps: remaining open questions and future researches

Limits of the adult fingerprint stability

As detailed in part 2.3, the experiment dataset did not comprise fingerprint data in the age range of 26-64. As a complementary and consolidating step such data will be required in order to confirm the following assumption based on the results of this report:

- Adults fingerprint quality and genuine matching scores are very stable between 18 and 40-45 years of age.
- At 40-45 years of age fingerprint quality and matching score start decreasing linearly.

Dedicated fingerprint quality metrics and matchers

As explained in Section 3.2.1, the quality metrics algorithms used in this study, were exclusively trained on adults' data. This is likewise the case for the vast majority of quality metrics proposed in the literature. As such, the incongruity pointed out in the report could be explained by the fact that quality metrics designed for adults may be inaccurate when predicting the performance of children data.

Fingerprint matchers are as well typically trained and tested on adults' data. As such, they may be unable to extract to full extent all the discriminative features from children's fingerprints, even if these are of a good-enough quality. This lack of reliability could also be applicable to elderly fingerprints (e.g., if training data does not take into consideration fingerprints above 50 years of age).

To confirm this hypothesis, specific quality metrics should be developed for children and elderly and their results compared to those of standard adult metrics. Developing specific quality metrics and matchers adapted to the reduced size of children fingerprints could also significantly improve both their quality and their genuine matching scores.

Touchless sensor

Another promising line of research is the emerging touchless technology which could improve the quality and matching performance of elderly fingerprints. With current touch-based technology, moisturizing the fingertip skin prior to the acquisition can also potentially help to obtain images with better quality.

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List of abbreviations and definitions

AFIS Automated Fingerprint Identification System
BSI Bundesamt fur Sicherheit in der Informationstechnik
BKA Bundeskriminalamt(German federal police)
BMS Biometric Matching System
DHS Department of Homeland Security
Dpi Dots (pixels) per inch
EER Equal Error Rate
EP European Parliament
FAR False Acceptance Rate
FRR False Rejection Rate
FBI Federal Bureau of Investigation
FMR False Match Rate
FNMR False Non-Match Rate
FTA Failure to Acquire
FTE Failure to Enrol
NBIS NIST Biometric Image Software
NFIQ NIST Fingerprint Image Quality
NIST National Institute for Standards and Technology
SEF Servço de Estrangeiros e Fronteiras
VIS Visa Information System

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Annexes

Annex 1. Detailed description of the original dataset

NUMBER OF SAMPLES PER AGE (year-based) - CHILDREN																	
0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1790	4592	10846	15713	15994	19308	11398	9058	8736	12700	12728	14188	15920	16060	14584	14000	15486	16936

NUMBER OF SAMPLES PER AGE (year-based) - ADULTS							
18	19	20	21	22	23	24	25
19580	20544	21610	16829	15554	17088	18756	20566

NUMBER OF SAMPLES PER AGE (year-based) – ELDERLY I																	
65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82
2782	2370	2250	1958	2776	5560	5380	4788	4248	4062	3682	3028	2572	2168	1974	1706	1224	1086

NUMBER OF SAMPLES PER AGE (year-based) – ELDERLY II																	
83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98		
766	618	500	374	280	162	126	76	46	38	14	6	10	2	2	6		

Annex 2. Further details of the experiment dataset

The time difference between the first and last sample for the 156087fingers in the database that contain more than one sample is:

	NUMBER OF FINGERS							
	Time difference between enrolled and test samples (in years)							
	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8
Children (0-17)	565	1842	12891	7842	15226	49716	13090	1428
Adults (18-25)	1613	3525	2842	2193	7101	16012	2657	146
Elderly (65-98)	596	812	623	537	3007	10420	961	

The next tables show the distribution of data with regard to age and time difference between enrolments for those fingers that were enrolled more than once (same as the table above, but on a year-by-year basis):

- The table rows show the age group to which the finger belongs at the time of the first enrolment.
- The table columns show the age difference between the first enrolment and the last enrolment of the fingerprint. That is, for fingers with more than one sample, only the first and the last are considered. The first column indicates that the time difference between the two samples is less than 1 year. The second column indicates that the time difference between the two samples is between 1 and 2 years. And so on.

E.G., there are 3822 fingers that were first acquired at age 15 while the last enrolment was between 5 and 6 years later.

Therefore, these tables show the distribution of the fingerprint pairs used in the matching experiments.

CHILDREN

Time difference between samples

Age at first sample (years)	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	
0	2	34	479	297	429	322	88	13	0	1664
1	4	100	1159	1120	1245	426	128	26	0	4208
2	22	229	4484	2395	999	467	221	70	0	8887
3	10	656	5710	2665	1271	608	330	93	0	11343
4	31	53	49	110	781	3555	910	78	0	5567
5	26	52	56	95	819	3495	765	75	0	5383
6	33	56	46	68	621	2962	806	71	0	4663
7	28	25	41	72	648	3353	919	106	0	5192
8	27	36	54	70	641	3308	942	95	0	5173
9	44	43	41	58	530	2543	740	50	0	4049
10	28	32	51	56	470	2232	588	71	0	3528
11	31	71	67	81	723	3278	785	72	0	5108
12	32	66	88	109	871	3703	921	67	0	5857
13	28	80	67	93	980	3857	851	76	2	6034
14	50	72	93	111	990	3788	990	98	0	6192
15	51	68	96	130	991	3822	1006	123	0	6287
16	60	64	155	150	999	3865	1033	122	0	6448
17	58	105	155	162	1218	4132	1067	120	0	7017
	565	1842	12891	7842	15226	49716	13090	1426	2	102600

ADULTS

Time difference between samples

Age at first sample (years)	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	
18	121	255	259	287	1377	4843	1267	146	0	8555
19	115	300	299	287	1411	5193	1390	0	0	8995
20	162	385	386	419	1963	5976	0	0	0	9291
21	225	523	517	557	2350	0	0	0	0	4172
22	273	585	635	643	0	0	0	0	0	2136
23	308	658	746	0	0	0	0	0	0	1712
24	409	819	0	0	0	0	0	0	0	1228
25	439	0	0	0	0	0	0	0	0	439
	1613	3525	2842	2193	7101	16012	2657	146	0	36528

ELDERLY

Time difference between samples

Age at first sample (years)	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	
65	78	130	99	101	500	1511	142	1	0	2562
66	65	82	69	90	347	1256	101	0	0	2010
67	74	97	61	54	335	1092	101	1	0	1815
68	42	76	50	29	263	932	88	0	0	1480
69	40	64	40	56	216	907	83	0	0	1406
70	44	44	50	24	199	893	62	0	0	1316
71	29	44	36	30	169	708	56	0	0	1072
72	25	29	32	30	159	546	55	0	0	876
73	19	37	37	20	140	493	42	1	0	789
74	30	27	22	20	121	494	46	0	0	760
75	21	32	24	18	125	378	40	0	0	638
76	31	14	8	12	104	243	32	0	0	444
77	8	26	24	15	70	256	14	0	0	413
78	13	11	10	4	61	189	29	0	0	317
79	18	16	12	8	59	151	19	0	0	283
80	17	20	9	12	33	125	14	0	0	230
81	7	16	12	2	31	71	12	0	0	151
82	7	14	6	4	30	62	5	0	0	128
83	6	6	2	2	19	33	4	0	0	72
84	4	8	8	4	6	23	6	0	0	59
85	6	8	2	0	12	19	0	0	0	47
86	0	5	2	2	4	16	1	0	0	30
87	6	4	6	0	2	14	0	0	0	32
88	4	0	2	0	0	6	0	0	0	12
89	0	2	0	0	0	2	2	0	0	6
90	2	0	0	0	0	0	0	0	0	2
91	2	0	2	0	0	0	0	0	0	4
92	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0
94	0	0	0	0	1	0	0	0	0	1
95	0	0	0	0	0	0	0	0	0	0
96	0	0	0	0	0	0	0	0	0	0
97	0	2	0	0	0	0	0	0	0	2
98	0	0	0	0	0	0	0	0	0	0
	596	812	623	537	3005	10420	954	3	0	16959

Annex 3. Detailed results for age experiments

Quality:

Figure 31 shows a more detailed analysis of the children fingerprint quality: children1 (0-4) vs children2 (5-12) vs children3 (13-17). Adults fingerprint quality is given for reference.

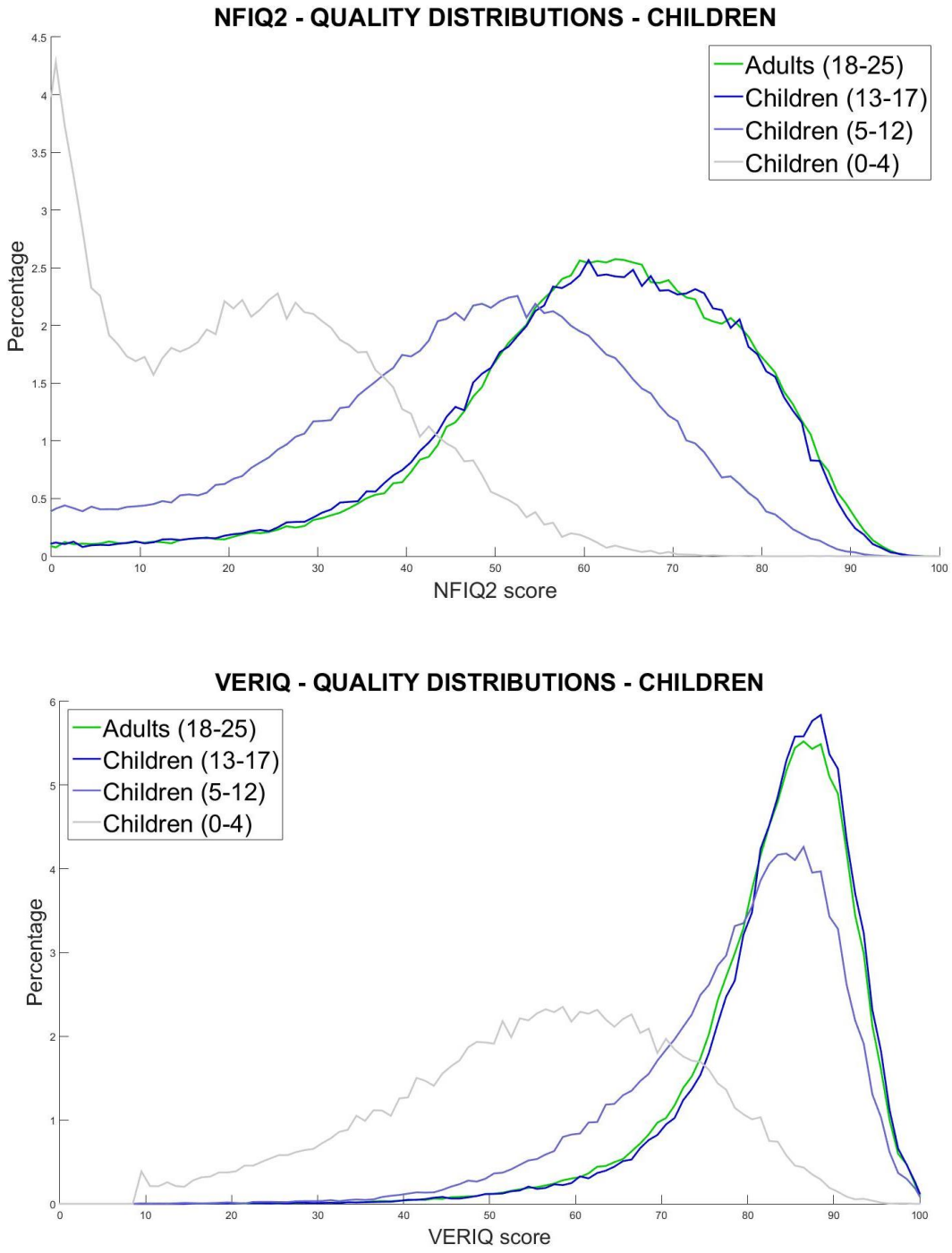


Figure 31 Comparison of the fingerprint quality of the three children sub-groups considered (i.e., 0-4, 5-12 and 13-17) according to NFIQ2, and VERIQ.

Figure 32 shows a more detailed analysis of the elderly fingerprint quality: elderly1 (65-69) vs elderly2 (70-74) vs elderly3 (75-79) vs elderly4 (80-84) vs elderly 5 (85 and above). Adults fingerprint quality is given for reference.

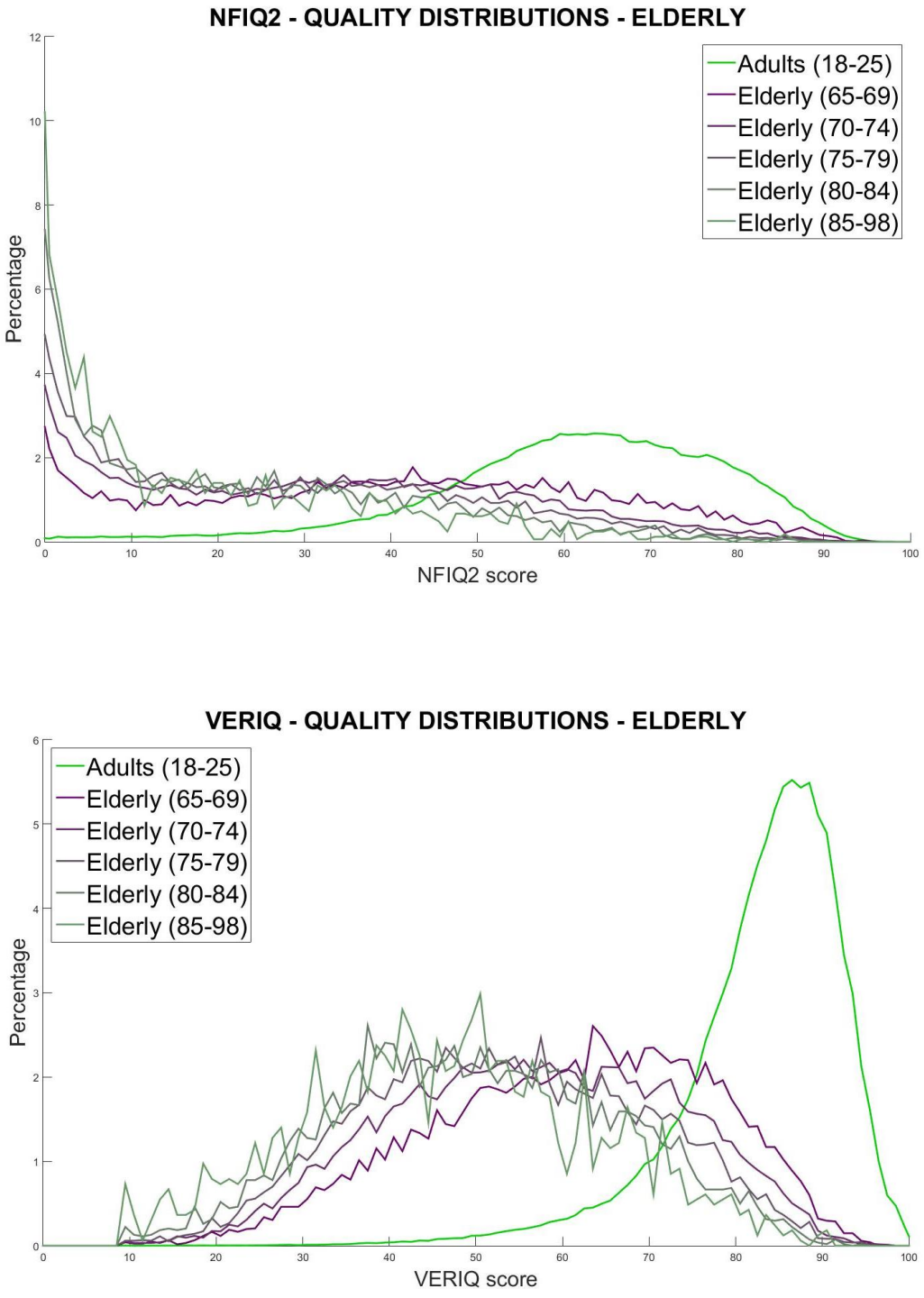


Figure 32 Comparison of the fingerprint quality of the five elderly sub-groups considered (i.e., 65-69,70-74, 75-79, 80-84 and above 85) according to NFIQ2, and VERIQ.

Matching:

Figure 33 shows a more detailed analysis of the children genuine scores: genuine score distributions of children1 (0-4) vs genuine score distribution of children2 (5-12) vs genuine score distributions of children3 (13-17).

Adults genuine score distribution is given for reference.

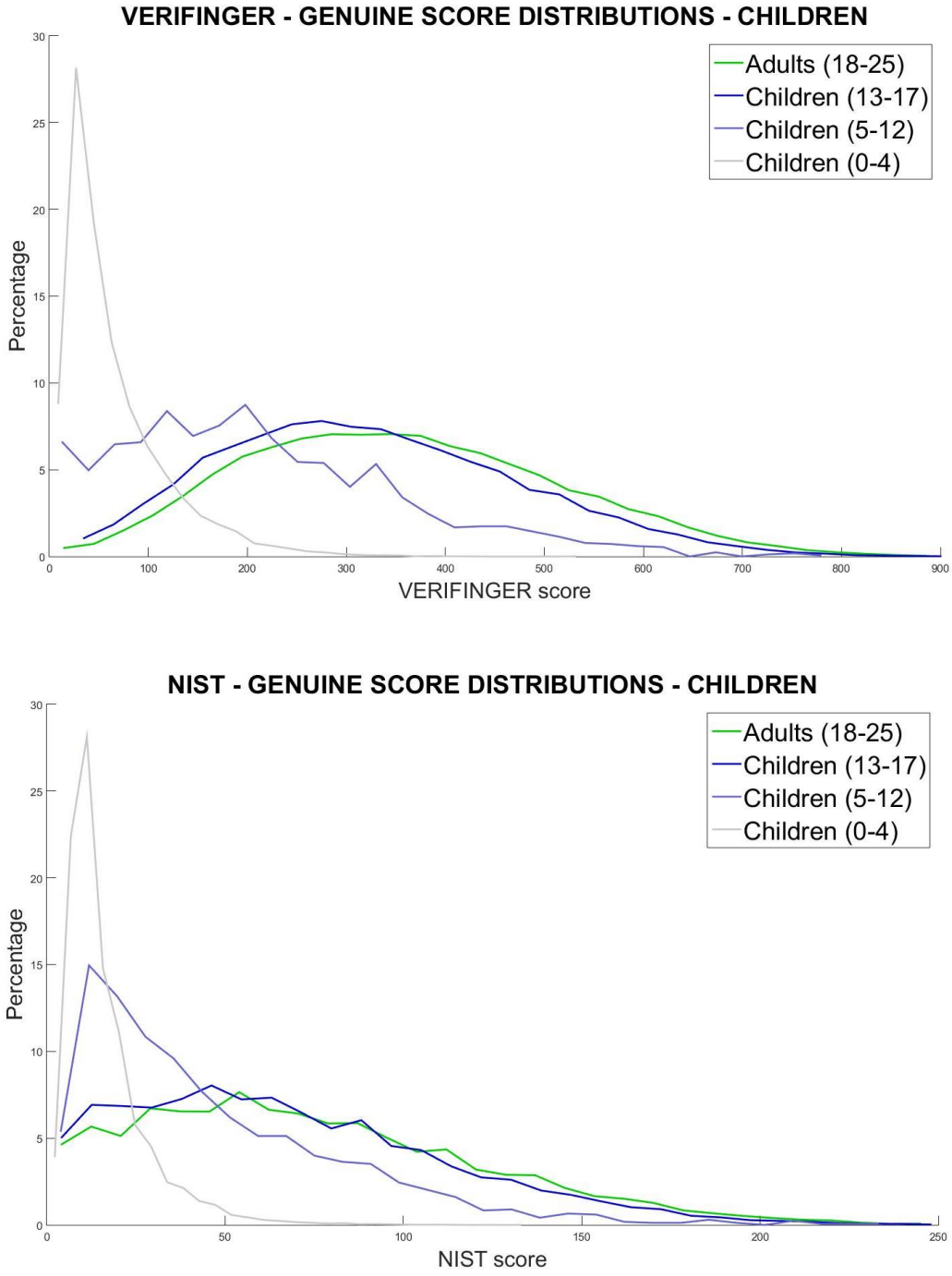


Figure 33 Comparison of the genuine score distributions of the three children sub-groups considered (i.e., 0-4, 5-12 and 13-17) computed with VERIFINGER and NIST.

Figure 34 shows a more detailed analysis of the elderly genuine scores: genuine score distributions of elderly1 (65-69) vs genuine score distribution of elderly2 (70-74) vs genuine score distributions of elderly3 (75-79) vs genuine score distribution of elderly4 (80-84).

Adults genuine score distribution is given for reference.

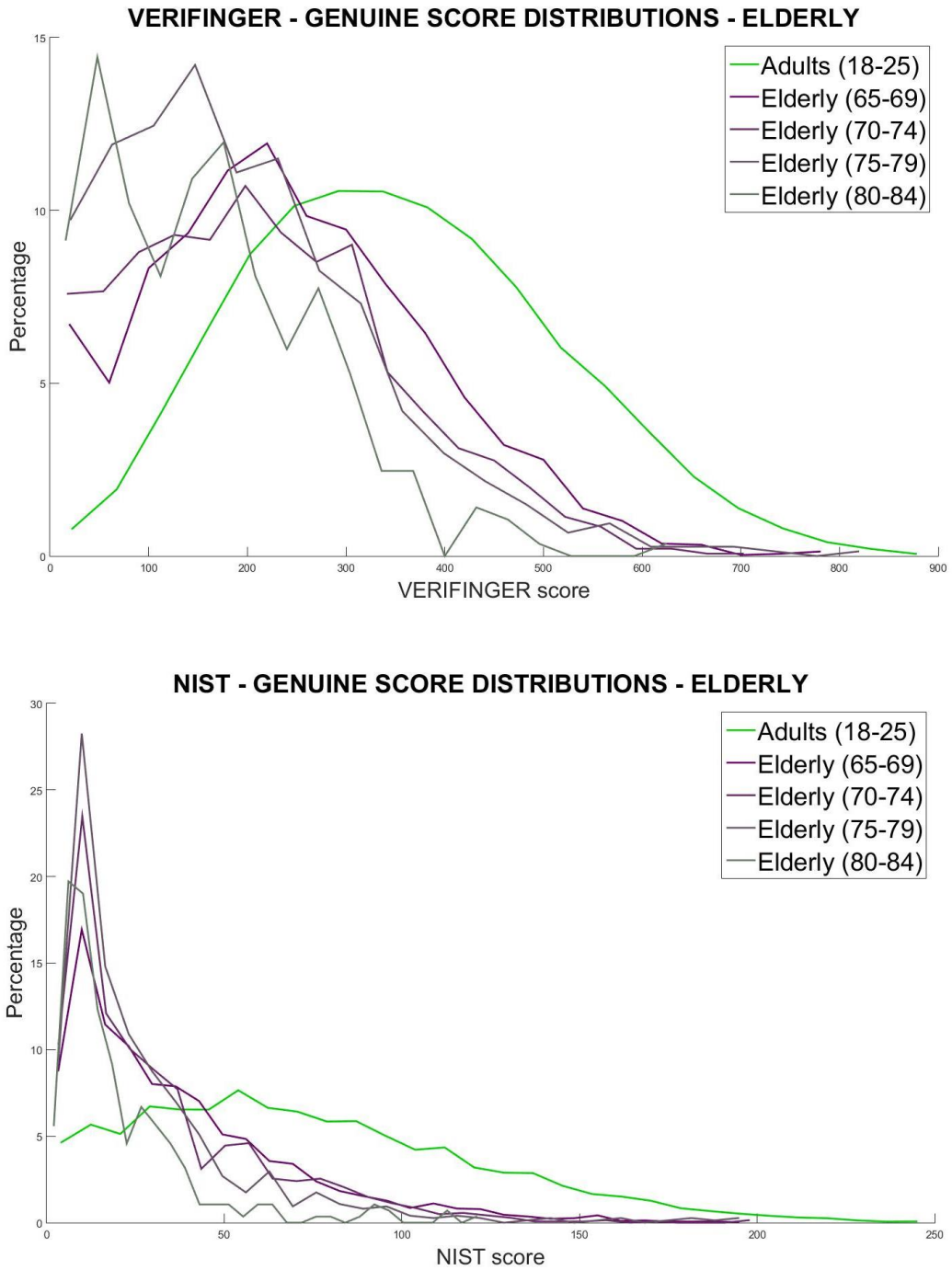


Figure 34 Comparison of the genuine score distributions of the four elderly sub-groups considered (i.e., 65-69, 70-74, 75-79 and 80-84) computed with VERIFINGER and NIST.

Annex 4. Detailed results for ageing experiments

Figure 35 and Figure 36 show, for the VERIFINGER and the NIST matchers, the eight genuine score distributions for age-groups: children1 (0-4), children2 (5-12), children3 (13-17) and adults (18-25). Each distribution corresponds to a difference between the enrolled and test sample of: 0-1 year, 1-2 years, 2-3 years, 3-4 years, 4-5 years, 5-6 years and 6-7 years. In all the plots the adults genuine score distribution for 0-1 years ageing is included for reference (in green).

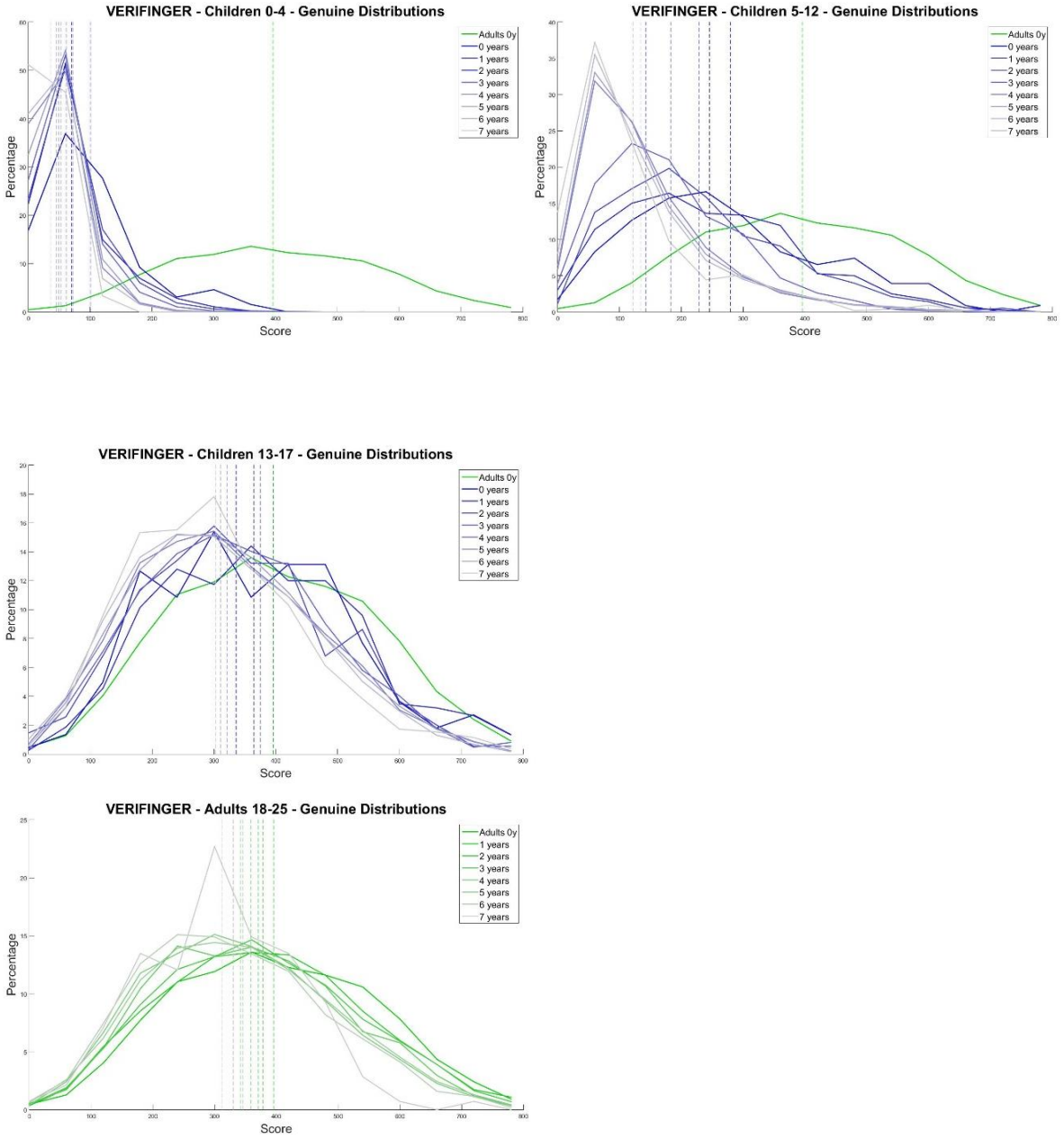


Figure 35 Genuine score distributions computed with VERIFINGER for age-groups: children1 (0-4), children2 (5-12), children3 (13-17) and adults (18-25).

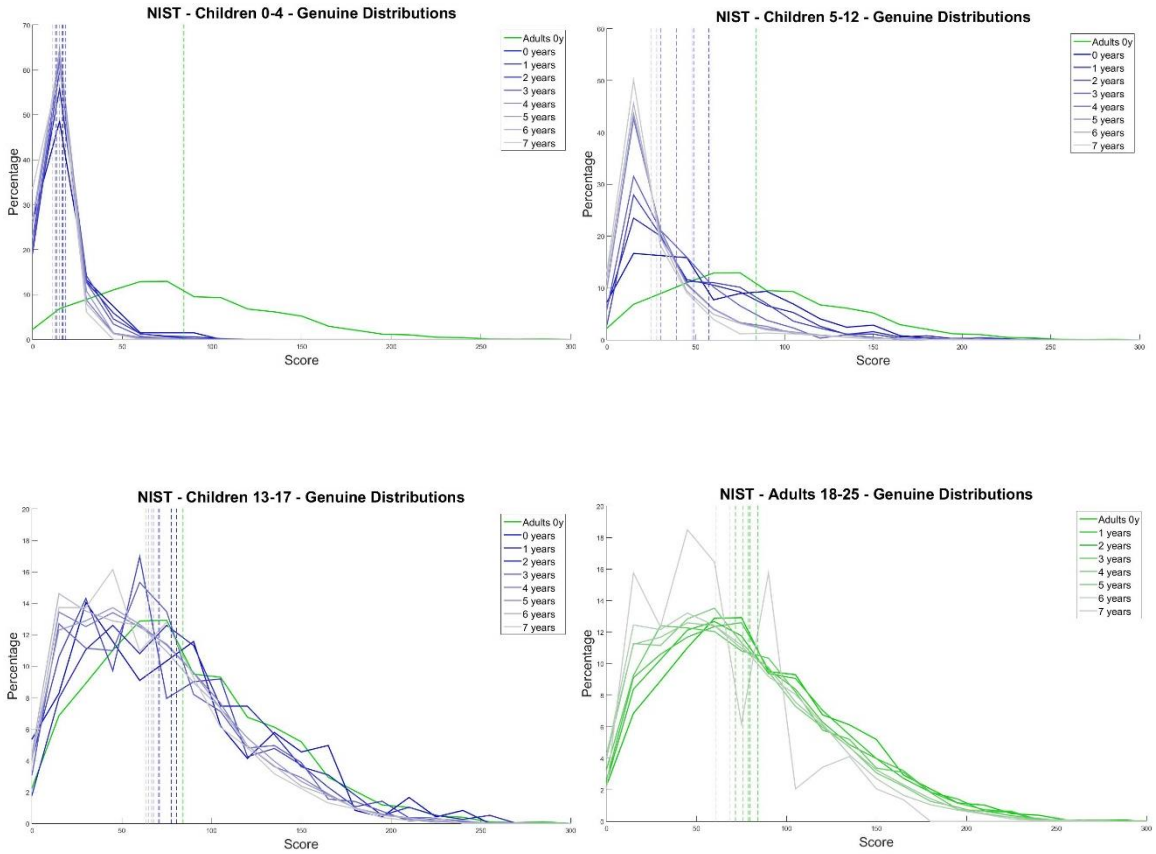


Figure 36 Genuine score distributions computed with NIST for age-groups: children1 (0-4), children2 (5-12), children3 (13-17) and adults (18-25).

Figure 37 and Figure 38 show, for the VERIFINGER and the NIST matchers, the eight genuine score distributions for age-groups: elderly1 (65-69), elderly2 (70-74), elderly3 (75-79) and elderly4 (80-98). Each distribution corresponds to a difference between the enrolled and test sample of: 0-1 year, 1-2 years, 2-3 years, 3-4 years, 4-5 years, 5-6 years and 6-7 years. In all the plots the adults genuine score distribution for 0-1 years aging is included for reference (in green).

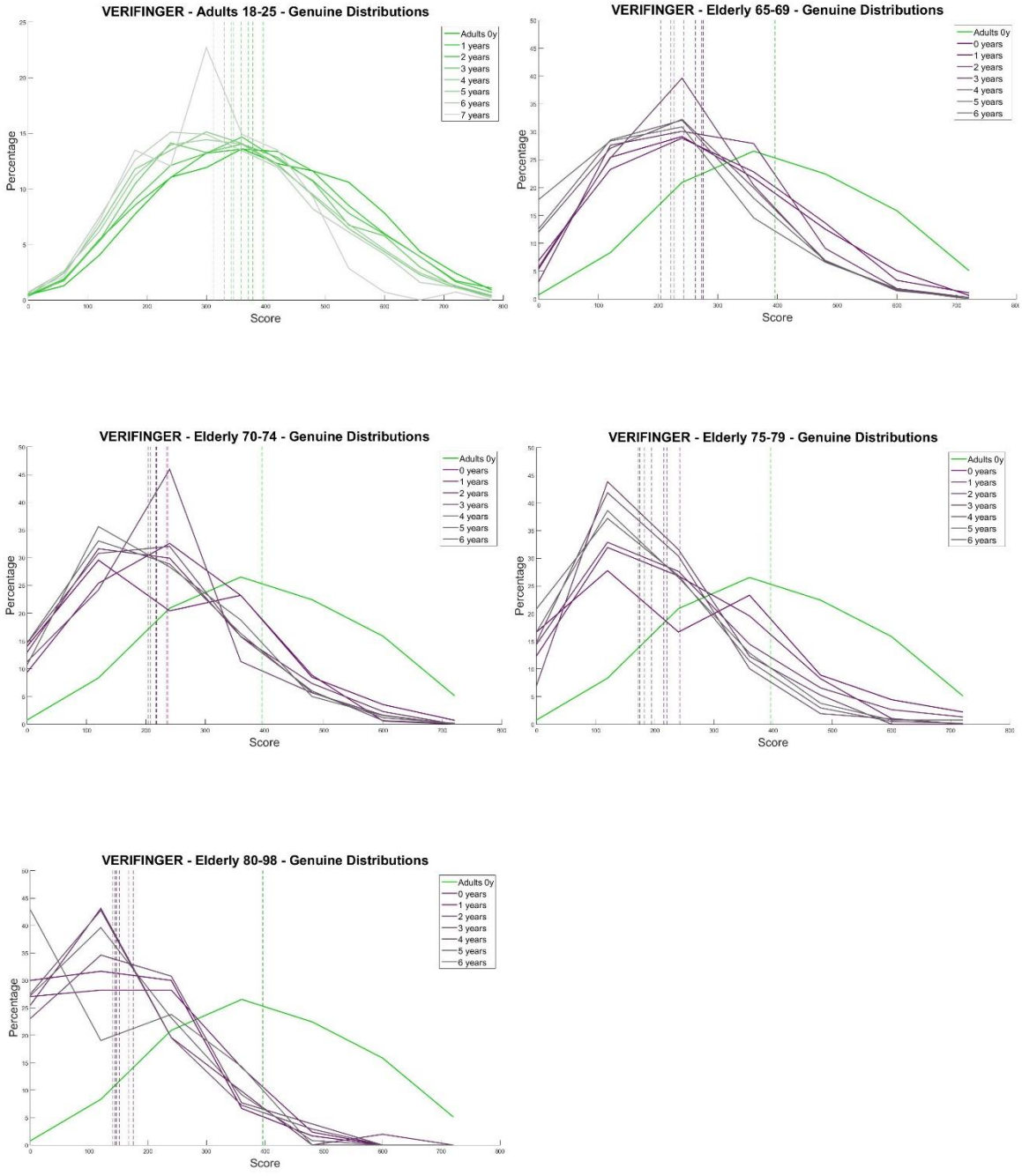


Figure 37 Genuine score distributions computed with VERIFINGER for age-groups: elderly1 (65-69), elderly2 (70-74), elderly3 (75-79) and elderly4 (80-98).

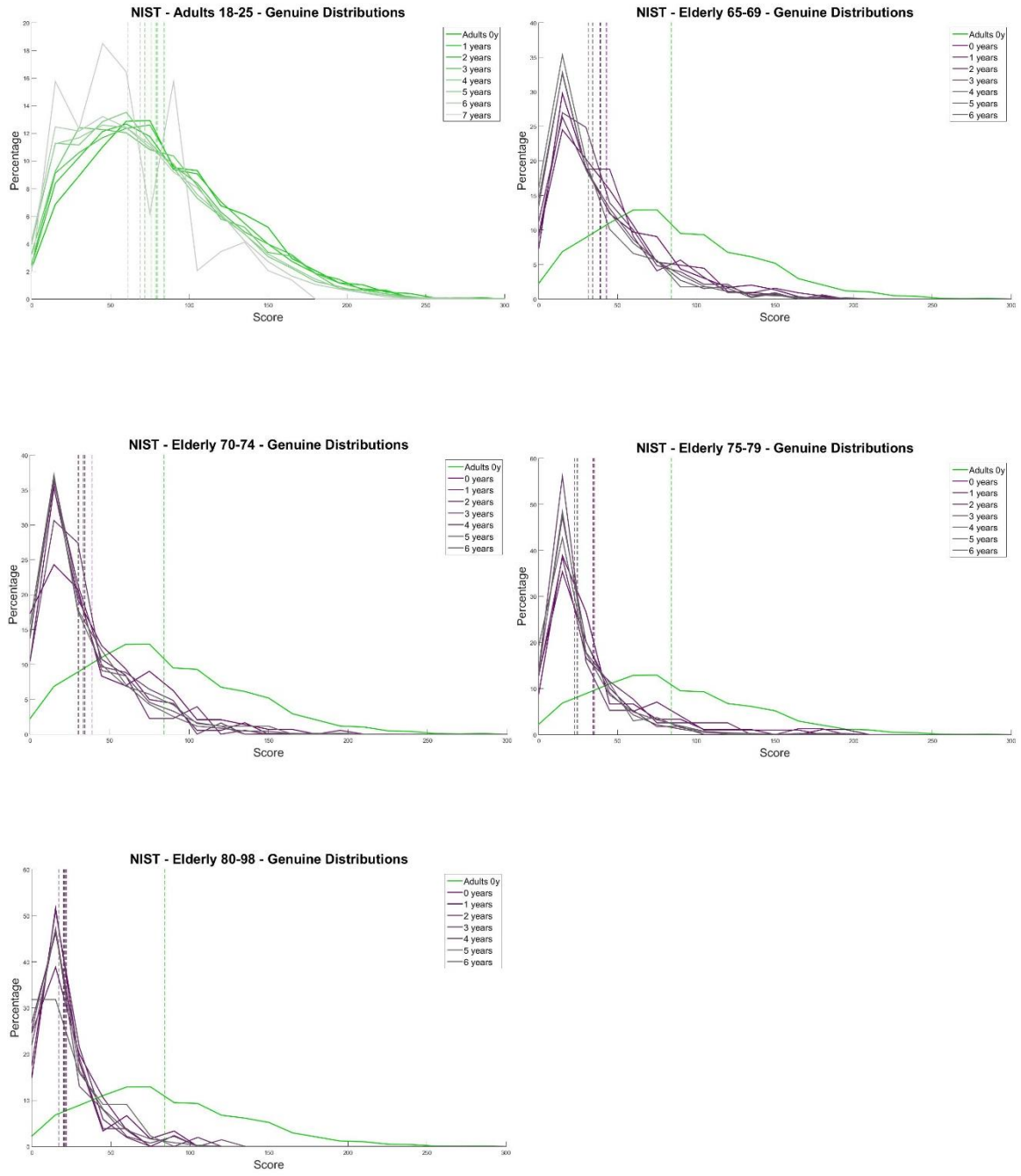
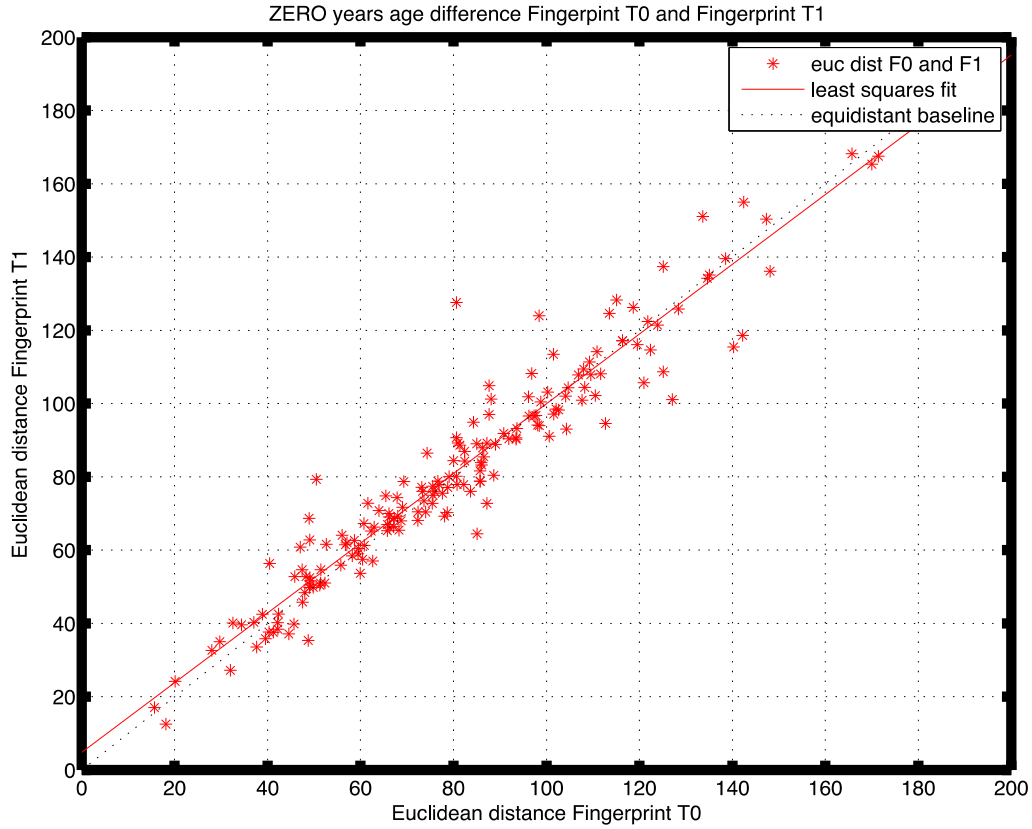
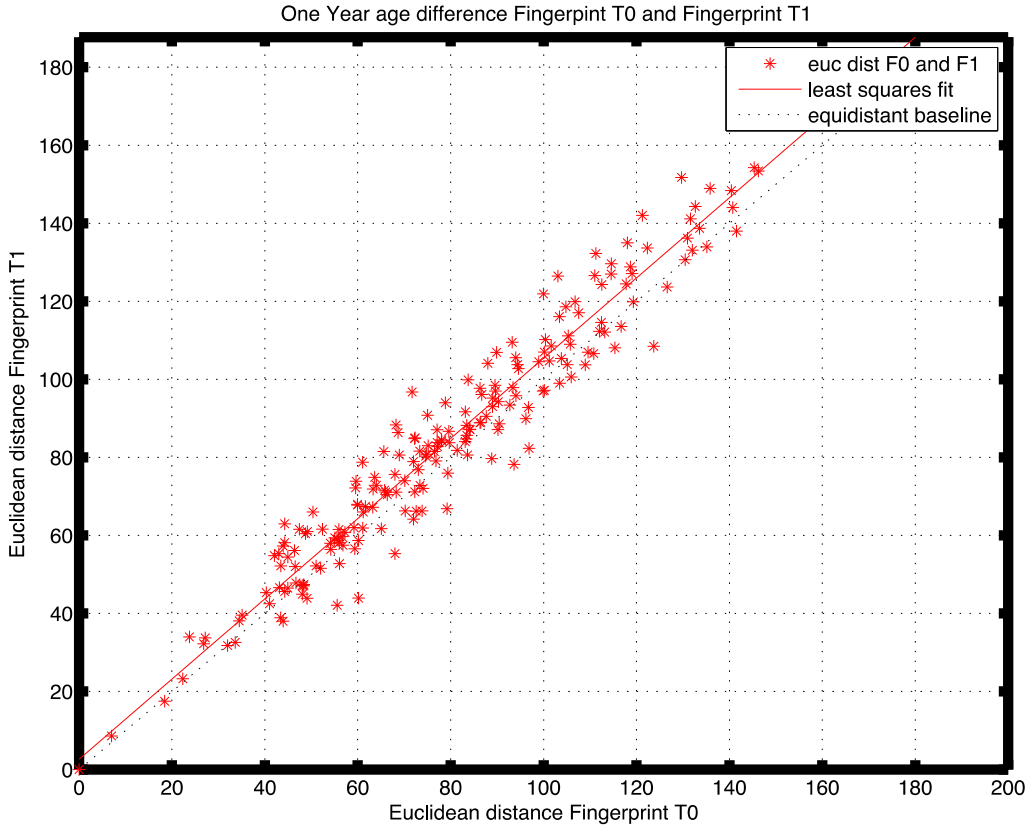
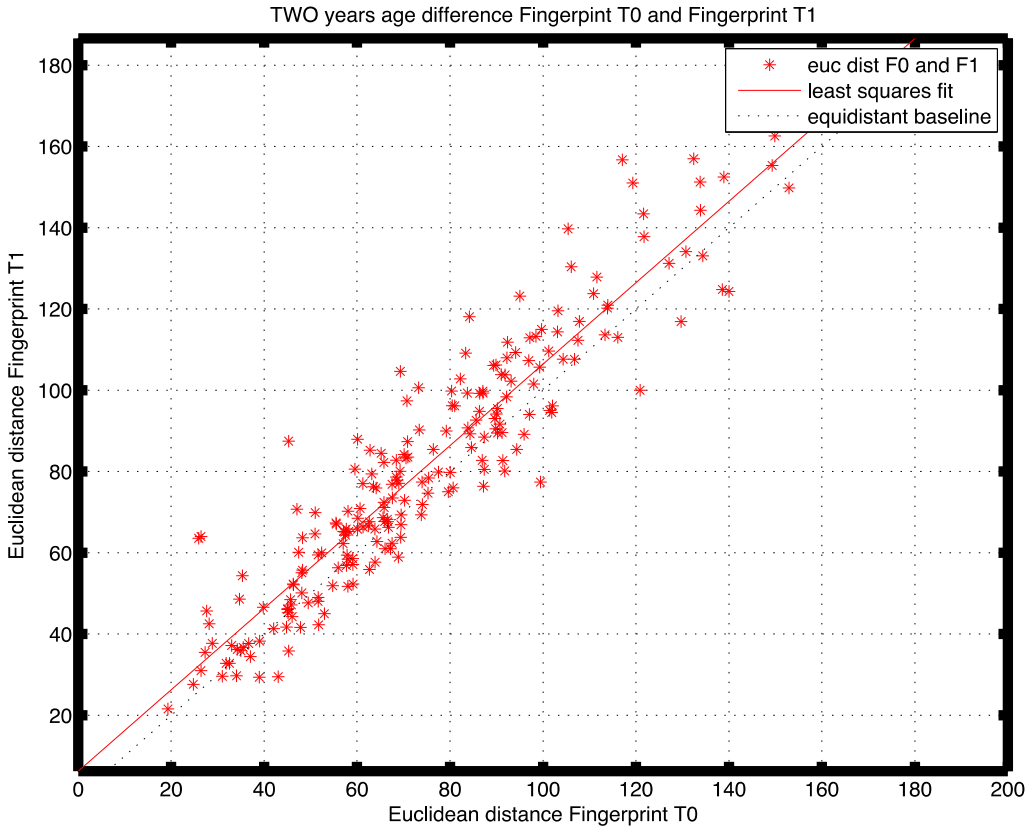


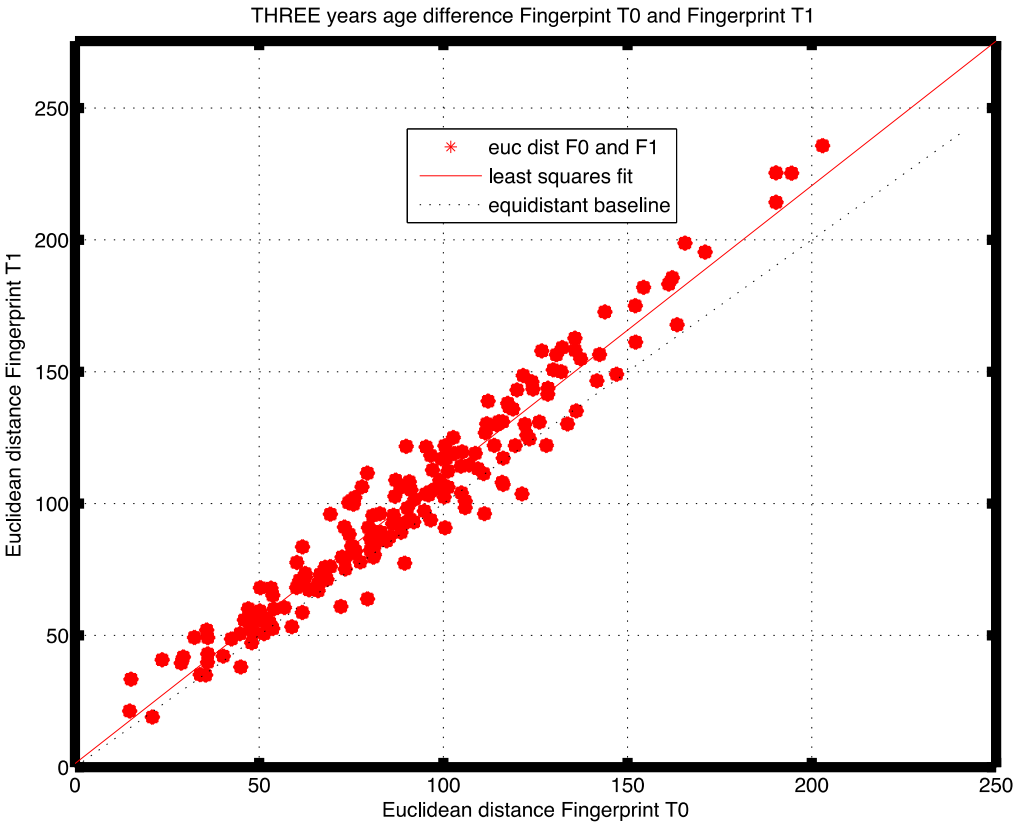
Figure 38 Genuine score distributions computed with NIST for age-groups: elderly1 (65-69), elderly2 (70-74), elderly3 (75-79) and elderly4 (80-98).

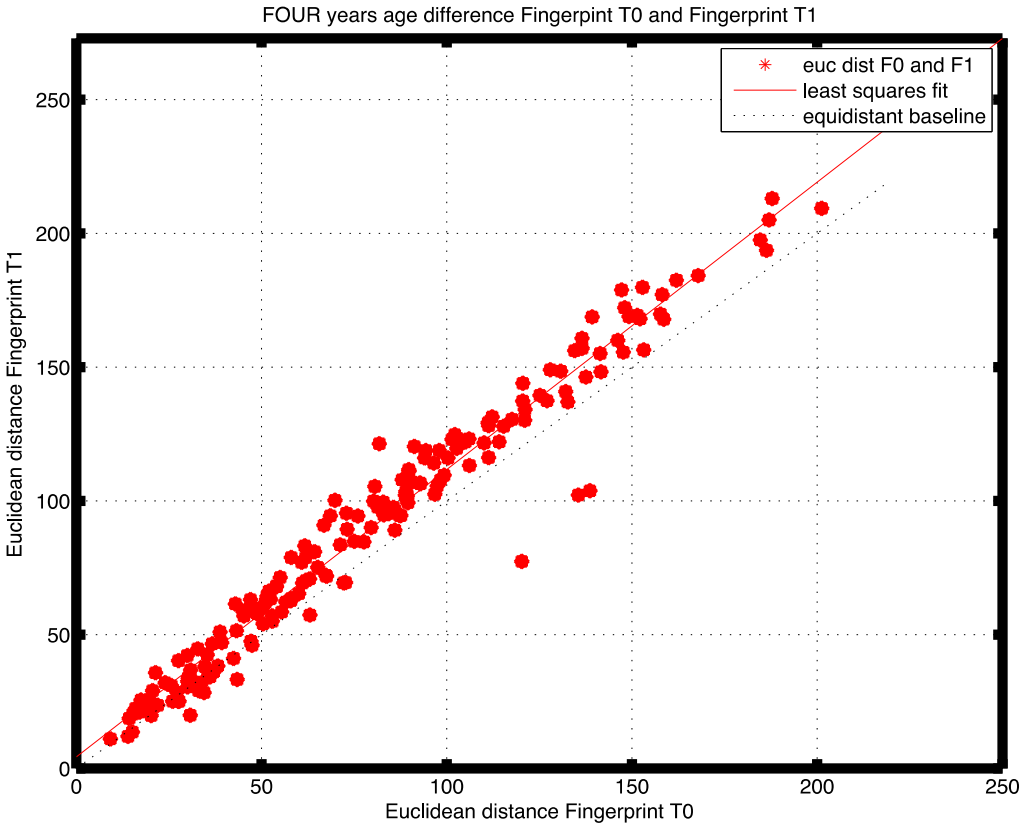
Annex 5. Examples of Euclidean distances evolution for the growth model in different categories

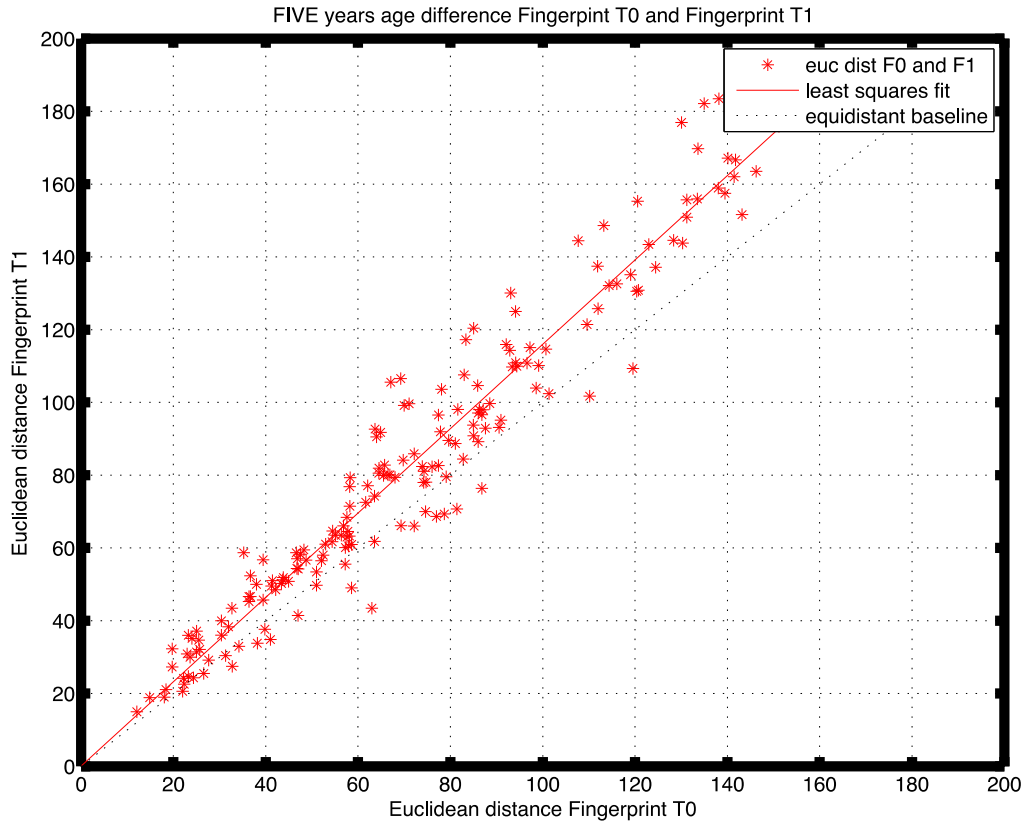





TWO years age difference Fingerpint T0 and Fingerprint T1
euc dist F0 and F1
least squares fit
equidistant baseline
Euclidean distance Fingerprint T1
Euclidean distance Fingerprint T0
0
20
40
60
80
100
120
140
160
180
200


THREE years age difference Fingerpint T0 and Fingerprint T1
euc dist F0 and F1
least squares fit
equidistant baseline
Euclidean distance Fingerprint T1
Euclidean distance Fingerprint T0
0
50
100
150
200
250


FOUR years age difference Fingerpint T0 and Fingerprint T1
euc dist F0 and F1
least squares fit
equidistant baseline
Euclidean distance Fingerprint T1
Euclidean distance Fingerprint T0
0
50
100
150
200
250


FIVE years age difference Fingerpint T0 and Fingerprint T1
euc dist F0 and F1
least squares fit
equidistant baseline
Euclidean distance Fingerprint T1
Euclidean distance Fingerprint T0
0
20
40
60
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100
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140
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180
200

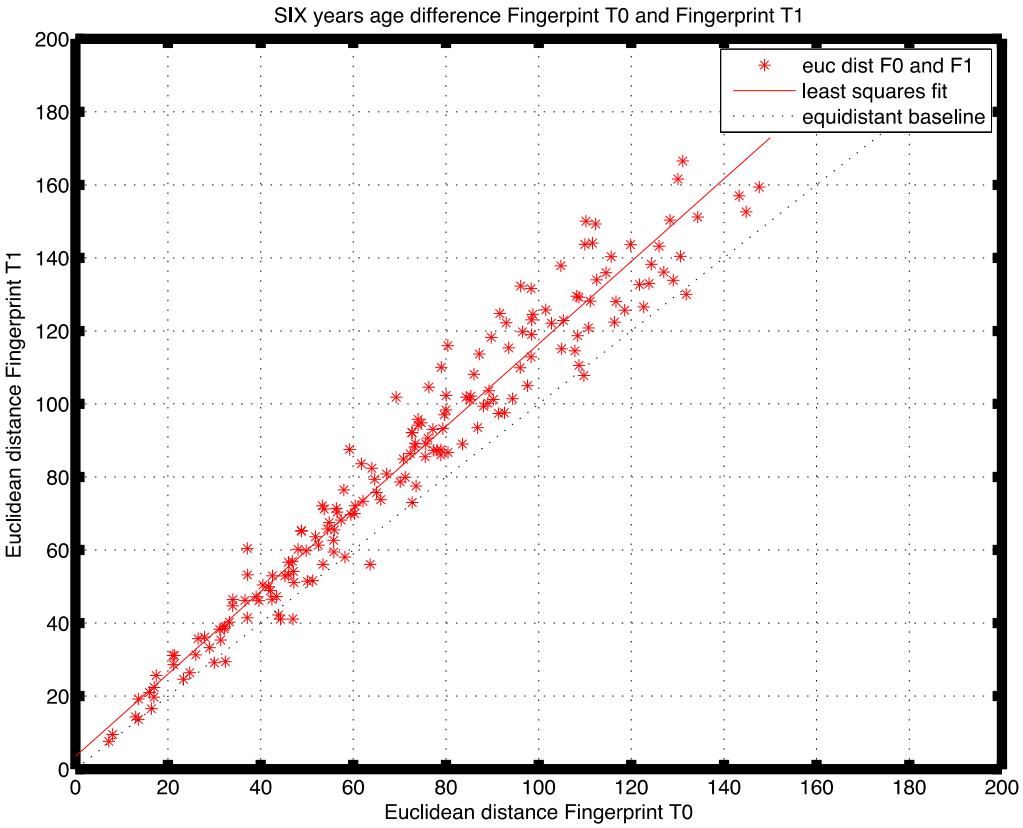

Figure 39 Euclidean distances of the pair of corresponding minutiae points and the centre of the origin per category related to the difference of the time in which the two fingerprints were enrolled.

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