Experimental Evidence of Ageing in Hand Biometrics

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Abstract: Biometric systems build upon the critical property of measuring behavioral, physiological or chemical human properties remaining stable over time. But both, the age of users and ageing of the user's template may affect performance due to the accumulation of personal changes and indirect behavioral effects like less accurate ability to present the biometric to the sensor. This paper compares short-timespan versus long-timespan effects on different hand-based features presenting the first high-resolution hand-ageing database and identifying features resistant and prone to ageing. Ageing goats, i.e. users responsible for low matching scores across features, are investigated and single-sensor multibiometrics is highlighted to target the ageing problem.

1 Introduction

From the prerequisites for biometric modalities proposed by Jain et. al. in 2004 [JRP04]: *universality* (availability of the property across populations), *distinctiveness* (high interpersonal variability), *permanence* (invariance over periods of time) and *collectability* (the characteristic can well be measured), it is the accumulation of changes in a person over time - ageing - affecting *permanence* which constitutes a major challenge to keep high performance of biometric systems. Especially for skin-related modalities, like fingerprints, hand geometry and palmprint, which dominate over 68% of the biometrics market [Int09] ageing is an important issue, since due to loss of collagen skin becomes dryer [MEWK07] and biometric signals may be extracted less accurately. While in the past, at many points claimed permanence and uniqueness properties of fingerprints, e.g. the claimed stability from the 24th week of gestation [GHL$^+$11] and uniqueness of fingerprints in 1892 [Gal92], have been questioned, like in the Brandon Mayfield fingerprint misidentification case in 2004, ageing effects have been superficially treated so far.

This work extends existing ageing studies focusing on the question *How does ageing affect different hand-based biometric features?* by providing a quantification of the impact on recognition identifying ageing-sensitive and ageing-invariant hand biometric features. The collected dataset is currently the only existing fingerprint and multibiometric full hand ageing dataset. It provides with 5 years timespan a 5 times larger time-lapse between recordings than comparable fingerprint-only datasets, like KFRIA [RJK07] (1 year, 100 subjects). In order to cope with the intrinsic problem of little test data in ageing (e.g. in [ABI05] "Np=30 people took part in the test", in [BG04] "experiments have been accomplished on a data set made of 30 subjects", or in [GHL$^+$11] "identification test was conducted [...] of all 48 subjects"), we employ significance tests. The novelty of the paper lies not only in setting ageing effects of different hand-based features into context, but to highlight the observation, that degradation is much higher than could be expected and second, that multibiometric fusion can target the ageing problem.

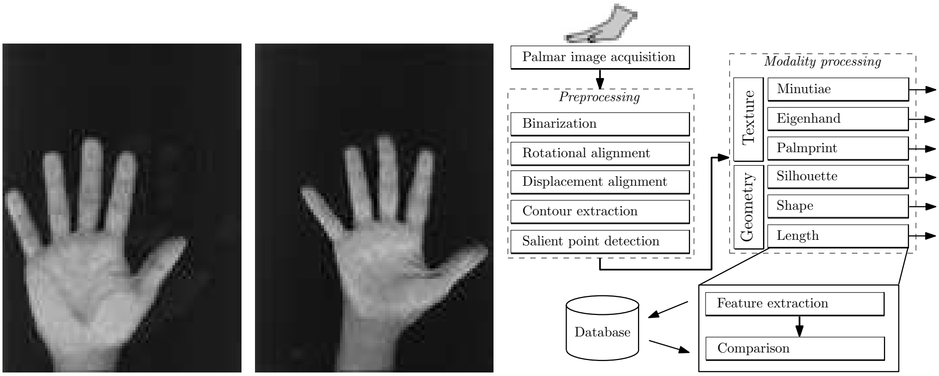
The paper is organized as follows: Section 2 presents related work. In Section 3 we introduce the multibiometric hand recognition system under test. Section 4 presents all experimental evaluations as well as employed ageing datasets and discusses ageing impact in detail. The paper concludes with a summary and outline on future research directions in hand biometric ageing in Section 5.

2 Related Work

Existing work in ageing mainly concentrates on the fingerprint modality. The impact of adult age groups (18-25, 26-39, 40-62 and 62+) on fingerprints recognition performance is highlighted by Modi et. al. [MEWK07] and in Uhl and Wild [UW09] for youth fingerprints (age groups 3-10, 11-18, 19+) observing overall a decreased performance for the boundary age groups, i.e. old and young fingerprints. Reasons for this behavior are given in Modi and Elliott [ME06] observing, that for age classes 18-25 vs. 62+ ageing causes global quality to decrease while false minutiae and the total average number of minutiae drastically increases (90 vs. 55). Sickler et. al. [SE05] show, that young fingerprints exhibit more moisture. As a solution to the problem of fingerprint age prediction Bevilacqua and Gherardi [BG04] watershed segment capacitance images and derive the sum of cells smaller than a given area (observing 13 pixels for 1 year age to 51 pixels for 91 years age). Uchida et. al. [UKM$^+$96] quantify skin ageing by analyzing the 3D profile of subjects aged 20-60 using 2D DFT features (assessing skin ridges) resulting in less high frequency components for elder people - but also wide scattering.

Besides cross-ageing tests, also the ageing of fingerprint features has been subject to investigations: Arnold et. al. [ABI05] quantify the degradation in fingerprint matching performance, using a long-term database from German federal criminal police office, as an FRR increase of factor 2 for 10 years time lapse. Ryu et. al. [RJK07] confirm the degradation observing an EER increase of a factor even greater than 2 over three sensors and a time delta of 1 year employing the KFRIA ageing database. In order to cope with age group effects, Gottschlich et. al. [GHL$^+$11] propose an isotropic rescaling method improving EERs from 11-14% to 5-6% for three different extraction and matching methods. Alternatively, template update techniques are common approaches in current biometric systems, like Kekre and Bharadi's [KB09] adaptive feature set algorithm, to account for intra-personal variability. Marcialis et. al. [MDP$^+$12] investigate self update algorithms providing a conceptual explanation using a path-based clustering view highlighting the critical task of selecting initial templates and the need for threshold relaxation in case of high environmental variability.

Related to other hand-based modalities, only few ageing studies exist. Uhl and Wild [UW09] extended their comparison of verification performance of kids and adults for fingerprints to also palmprint, hand-geometry and digitprint biometrics resulting in sim-



(a) #6 (b) #32 (c) #32

Figure 1: Sample full-hand images of (a) 24-year-old male user #6 in session 1 (b) 54-year-old female user #32 in session 2 and (c) Architecture of the tested multibiometric system.

ilar results - i.e. age degradation for the youngest age group with only few exceptions - like an inverse behavior for the hand geometry feature. Lanitis et. al. [LT11] investigate template-ageing for face, fingerprint, and palm modalities and formulate a generic AI factor metric assessing the impact of ageing. According to their experiments on FG-NET face ageing and POLYBIO2 multibiometric (face, fingerprints, speech, palm) databases, features derived from faces tended to cause highest AI factors, followed by palm-based features and fingerprints - yet no direct impact on recognition accuracy is provided. Zheng et. al. [ZjWB07] investigate biometric features in hand geometry that are both distinctive and invariant to projective transformations, therefore can be expected to tolerate more variation - caused by, e.g., ageing effects.

Latest trends in fingerprint-based biometrics propose the extraction of fingerprints from full-hand images, employing either high-resolution scans [UW09] or even extracted from video [QYRL10]. In favor of traditional single finger optical, capacitive, ultrasound and thermal single sensors, multi-biometric hand-based acquisition from a single sensor has the advantage, that all hand-based modalities can be extracted at the same time - even by using commodity hardware. This way, accuracy can be further increased by employing fusion techniques. Especially for ageing societies ageing effects causing failures to enrol or false accepts and rejects may decrease the acceptability. Therefore, the approach involving multiple biometric traits is also favored by Rebera and Guihen [RG12] assessing the social impact of biometric ageing.

3 System

We assess the age impact on three textural and three geometrical hand-based features related to the modalities fingerprint, digitprint, palmprint and hand-geometry, described in the following subsections. All these modalities are extracted from a single high-resolution (500 dpi) scan of the palmar surface of the hand using commodity flatbed scanner hardware (HP Scanjet 3500c), see Fig. 1. We extract: (1) minutiae from regions of interest

(ROI) at finger tips; (2) digitprints of individual fingers; (3) a palmprint ROI using again a fixed size region centered in the middle-ring finger valley, and (4) the entire hand image.

Preprocessing segments skin from background using Otsu's thresholding [Ots79], the largest connected object is rotationally aligned using moment-based ellipse fitting. Contour extraction is based on the center-of-mass, detected salient points are used to map the image onto palm coordinates [UW09]. We employ the valley between middle and ring finger as origin and use an approximation of the outer palm line for orientational alignment. Fingers separated by valley positions are fitted with ellipses. Geometrical and textural features operate on either contour data or ROIs.

3.1 Fingerprint Extraction and Comparison

We employ local (level-2) fingerprint features [MMJP09], i.e. minutiae tracking position (x, y) and orientation (θ) of *bifurcations* and *terminations* of ridge lines. For this task, NIST's *mindct* extractor [NIS06] has been employed on the normalized (CLAHE) finger-axis-aligned fingerprint patches using a fixed fraction of the finger's length (one third of its height, one half for the thumb) as ROI. For comparison, we employ NIST's *bozorth3* comparator and combine results of each finger using sum rule fusion.

3.2 Digitprint Extraction and Comparison

As digitprint textural feature we employ the classical Turk-Pentland [TP91] Eigenspace-based feature extraction method projecting each finger (and the palmprint) onto the space spanned by the 25 most significant principal components, trained from a separate dataset. Since this method exploits similarities at low resolution employing a compact representation minimizing the reconstruction error tracking the projection coefficients as feature vectors, it may be more robust to ageing changes than other features. Comparison is executed in the domain of Eigenspace coefficients employing the L_1 norm on the template vectors and product rule fusion to combine all fingers and palm.

3.3 Palmprint Extraction and Comparison

For the palmprint region we extract both, an Eigenspace-based feature (see Sect. 3.2) as well as a local block-based variance feature. The first feature is fused with digitprints to contribute to a common Eigenhand feature. The latter follows Kumar et. al. 's approach [KWSJ03] tracking 144 variances of overlapping 24 times 24 pixel sized blocks and is applied to a mean-variance normalized square (using the average finger length as unit length) palmprint edge region (using Prewitt filtering), centered in the finger valley between ring and middle finger at an offset of 0.2 times the finger length. Two feature vectors are compared based on the L2 norm.

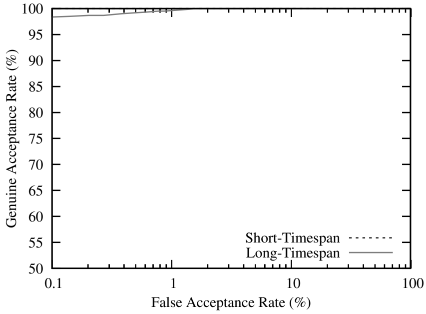
3.4 Hand-Geometry Extraction and Comparison

Kukula and Elliott [KE06] investigate hand geometry as one of the oldest (since 1960s) commercialized modalities and report high acceptability (93%), high universality (0% FTE) and high accuracy (0.98% FRR) for a test set of 129 persons. Common measures relate to widths and height of fingers, palm, segments, etc. in the order of 10-30 features [JRP99, SRSAGM00, KWSJ03]. Geometric features are known to be less suited for identification, but can effectively be employed for fast screening and additional plausibility checks in order to strengthen security (it is generally believed that a multibiometric system is more difficult to circumvent than unimodal systems, although the attacker may specifically target the weakest biometric). Especially for ageing, it is interesting to verify claimed fragility of geometry-related measurements. The employed hand geometry feature tracks all 5 finger lengths (including segment lengths of proximal, intermediate and distal phalanx), finger silhouettes (contours as distances with respect to the finger's centroid and enclosed area) and a shape-based feature. The latter feature takes local finger widths (scans of the y-monotone finger contour building for each slice the average width of in-object pixels in a total of 15 components) into consideration. As comparators the L1 norm for finger shape, dynamic time warp matching [MR81] of the silhouette and L2 norm for the finger length, respectively, are employed.

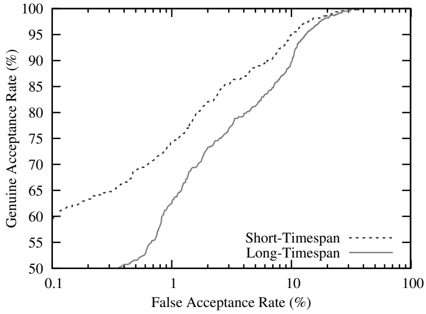
4 Experiments

For ageing experiments, we collected a database of high-resolution human handprints from 28 members in our labs with 127 hand images in the first session (Old) captured in November 2007 and 135 hands in the second session (New) captured in October/November 2012, i.e. exhibiting a time lapse of approximately 5 years between recordings adhering to the same strict recording protocol (users were allowed to wear rings or watches and obtain an arbitrary position on the scanner as long as fingers did not touch each other)[1]. The system is initialized (parameters for preprocessing, training of feature space) using data from a separate dataset involving a distinct person set (i.e. for the calculation of Eigenfingers and Eigenpalms). Performance is evaluated in terms of pairs of Genuine Acceptance Rate (GAR) at certain False Acceptance Rate (FAR) in form of receiver operating characteristics (ROC) to compare different features under ageing effects. We chose the Equal Error Rate (EER), i.e. the operating point with equal FAR and FRR=1-GAR as main comparison criterion. For the estimation of statistical significance of results, McNemar tests [Yat84] are conducted. In the following subsections several claims related to ageing are examined.

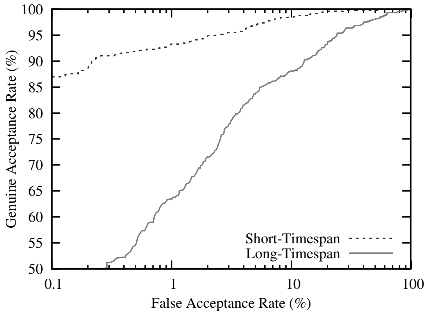
[1] see `http://www.wavelab.at/sources/Uhl13b` for available material related to this study.



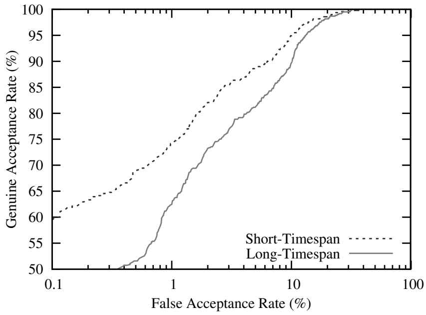
(a) Minutiae



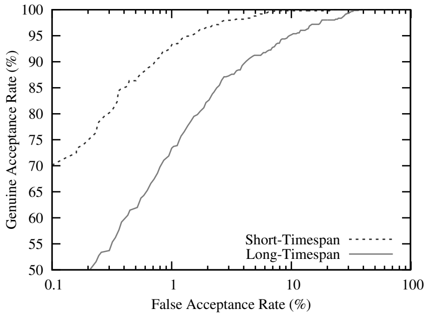
(b) Eigenhand



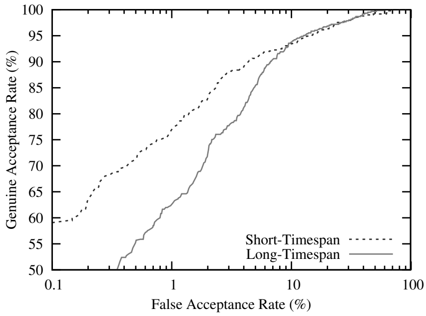
(c) Palmprint



(d) Silhouette



(e) Shape



(f) Length

Figure 2: ROC curves for template-ageing effects on hand-based features.

Table 1: Ageing-effects on EER

Feature	EER Short	EER Long	X^2 McNemar
Minutiae	0	0.63 %	12.02
Eigenhand	1.22 %	1.22 %	1.35
Palmprint	3.95 %	11.40 %	35.40
Silhouette	7.81 %	10.12 %	8.38
Shape	2.55 %	7.15 %	39.75
Length	7.67 %	8.10 %	0.03

Table 2: Short-Timespan ageing effects

Feature	EER 2007	EER 2012	X^2 McNemar
Minutiae	0	0 %	n/a
Eigenhand	1.3 %	0.8 %	2.04
Palmprint	3.4 %	4.5 %	1.26
Silhouette	8.5 %	7.3 %	3.32
Shape	3.7 %	1.3 %	9.19
Length	7.2 %	7.5 %	2.56

4.1 Claim 1: "Hand-ageing has no statistical significant impact on recognition"

In order to disprove claim 1, we compared short-timespan (1 day) and long-timespan (5 years) performance of individual features. We therefore examined comparisons of 491 (605) genuine and 16288 (16286) imposter pairs of handprints (numbers in brackets refer to long-timespan pairs). From the ROC curves in Fig. 2 and error rates in Table 1 we can see, that for all of the employed features, an increased time-span of 5 years between recordings decreases recognition accuracy over almost the entire operating range for almost all features. Still, in the interesting EER range ageing impact on some of the features was less expressive. Claim1 disproved.

4.2 Claim 2: "Within a modality, ageing has comparable impact on features"

Comparing classifiers based on thresholds set to achieve close-to-EER performance and using a 95% confidence level (3.84), Minutiae, Palmprint, Silhouette, and Shape classifiers are significantly affected by ageing, while the longer timespan showed no significant effect on Eigenhand and Length features. In order to be able to conduct McNemar significance testing we relate short-timespan and long-timespan comparisons by exchanging the probe template p_i in the gallery-probe pair (g_j, p_i) by the corresponding i-th sample of the parallel session. Furthermore, for balancing reasons, we restrict imposter comparisons to the same amount of genuine comparisons and test the classifier in close-to-EER setup based on training data.

Especially for the highly accurate Minutiae feature providing perfect separation for short-timespan data, the long-timespan comparison yields errors due to ageing effects: 0.63% EER. Interestingly, system error increase is observed to be least significant for the Length feature (7.67% vs. 8.10% EER, respectively) tracking finger lengths - a feature which is known to be rather varying during bone growth. However, it has to be considered, that original matching rates are already quite high. For similar reasons, the Silhouette feature is only slightly degraded from 7.81% to 10.12%. Besides for high-security configurations, Eigenhand provides both, high accuracy and no significant changes (stable 1.22 % EER

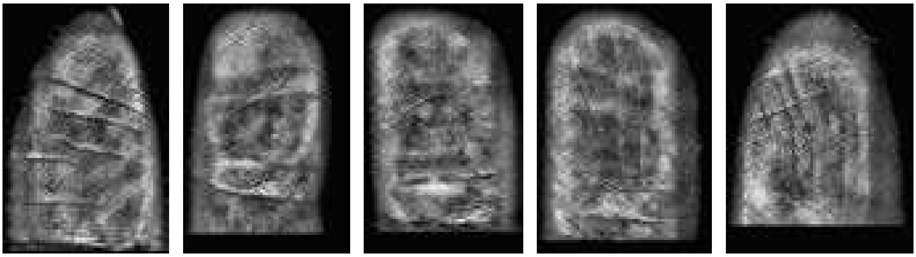
Table 3: Users responsible for 5% lowest match scores (numbers in brackets indicate repeated appearance)

	2007 vs. 2012
Minutiae	#32 (20), **#30** (7), #15, #12, #24
Eigenhand	#21 (9), #14 (6), #6 (4), **#30** (3), #15 (3), #13 (3), #12, #16
Palmprint	#31 (6), #7 (5), #12 (5), **#30** (3), #13 (3), #10 (2), #28 (2), #4, #1, #9, #21
Silhouette	**#30** (5), #31 (5), #10 (3), #4 (3), #16 (3), #19 (3), #14 (2), #6 (2), #28 (2), #12, #9
Shape	#21 (15), **#30** (6), #12 (4), #14 (4), #8
Length	#6 (13), #18 (7), **#30** (4), #14 (3), #31, #13, #16
	2007
Minutiae	#24 (4), #15 (3), #12 (3), #30 (2)
Eigenhand	#6 (4), #14 (3), #10 (3), #21, #16
Palmprint	#7 (3), #21 (2), #18 (2), #14, #12, #31, #1, #16
Silhouette	#19 (3), #6 (2), #31 (2), #16 (2), #10, #9, #30
Shape	#30 (4), #14 (3), #19 (2), #9, #31, #12
Length	#6 (6), #18 (4), #10, #7
	2012
Minutiae	#32 (9), #24 (3), #30
Eigenhand	#13 (5), #6 (3), #31 (2), #30 (2), #11
Palmprint	#26 (4), #31 (3), #13 (2), #1, #21, #7, #12
Silhouette	#6 (4), #4 (3), #31 (2), #11 (2), #29, #13
Shape	#30 (6), #8 (2), #31 (2), #32, #22
Length	#6 (6), #18 (3), #13 (2), #31, #32

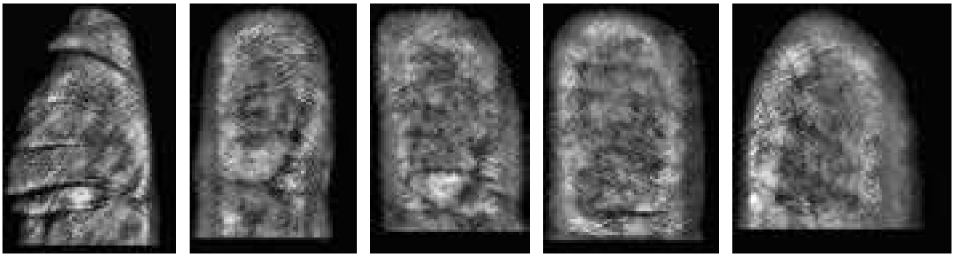
and $\chi^2 = 1.35$ in the McNemar test). Due to fusing results from 5 fingers and palm this feature benefits of using multiple geometric and textural properties from various different parts of the hand. Palmprint with 11.4% EER and Shape with 7.15% turned out to be most affected (degradation greater than factor 2). Claim 2 disproved.

4.3 Claim 3: "Short-time intra-personal variability increases with age"

Since [UW09] report different age group performance of youth handprints, we examined intra-short-timespan performance of the two session recordings in 2007 and 2012. Results are given in Table 2. While some features even exhibited higher accuracy for 2012 data compared to 2007, performance differences were not pronounced and McNemar significance tests yielded no significant performance differences for all but the Shape feature. Furthermore, in this configuration the number of genuine comparisons is halved compared to the short vs long-timespan experiments. Therefore, there may be intra-session ageing effects, but Claim 3 could not be confirmed using the given datasets. On the other hand, results confirm validity of the experimental configuration, i.e. set 2012 is not "more challenging".

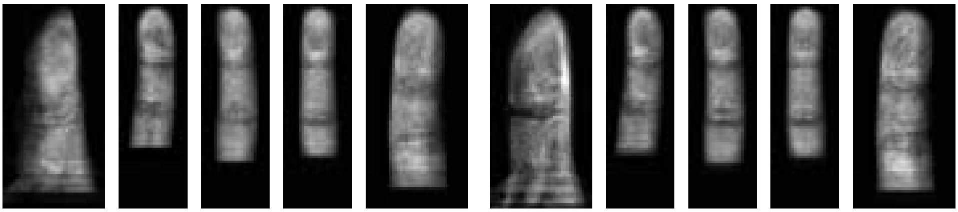


(a) Thumb (b) Index (c) Middle (d) Ring (e) Little



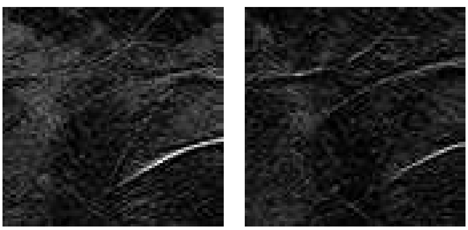
(f) Thumb (g) Index (h) Middle (i) Ring (j) Little

Figure 3: Long-Timespan 2007 (a-e) and 2012 (f-j) Minutiae genuine pair illustrating age variation due to false minutiae detected near changed creases and worn fingerprints.



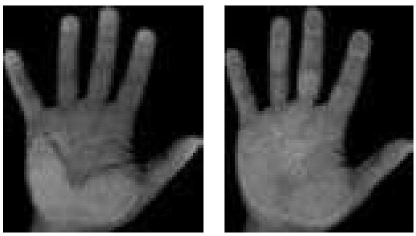
(a) Thumb (b) Index (c) Middle (d) Ring (e) Little (f) Thumb (g) Index (h) Middle (i) Ring (j) Little

Figure 4: Lowest scored Eigenfinger Long-Timespan 2007 (a-e) and 2012 (f-j) genuine pair still closely resembles original data.



(a) Palm 2007 (b) Palm 2012

Figure 5: Low-scored Palmprint genuine pair (more expressive wrinkles).



(a) Hand 2007 (b) Hand 2012

Figure 6: Low-scored Shape and Silhouette Long-Timespan genuine pair (thicker fingers).

4.4 Claim 4: "Short-term goats extend to long-term goats"

Related to Doddington's [DLM+98] classification of users, we investigated by analyzing users responsible for the 5% of lowest matching scores (see Tab. 3), whether short time *goats* (users exhibiting problems in being accepted) extend to long-time goats. For this experiment we separately analyzed 236 and 255 genuine as well as 7765 and 8523 imposter comparisons, respectively for each of the sessions 2007 and 2012 (short-timespan) and 605 genuine and 16286 imposter comparisons for the cross-session (2007 vs. 2012) experiment. We found, that: (1) there are users with low matching scores across all features, e.g. # 30; (2) many short-term goats are also long-term goats (100% of lowest-5%-scored Minutiae users, 78% for Eigenhand, 60% for Palmprint, 73% for Silhouette, 44% for Shape and 57% for Length) confirming Claim 4, and; (3) between features rather different users cause problems suggesting for efficient fusion.

4.5 Discussion

From examinations in previous sections, we see, that increased time variation has significant impact on recognition accuracy. Still, one might object, that by measuring the impact of time variation also factors other than age - like dirt, bruising or growing nails may affect recognition accuracy. By adhering to the same strict attended recording protocol and assessing also intra-session effects, we tried to minimize other influencing factors. However, in order to highlight ageing factors, this section illustrates some of the observed visual effects. In Fig. 3 showing a long-timespan genuine tenprint we see (1) the problem of additional/different creases leading to false minutiae, and (2) worn fingerprints (especially Middle and Index). Fig. 4 illustrates the lowest-score Eigenfinger pair highlighting that low resolution does not track skin wrinkles and dryness, in contrast to e.g. the higher-resolved Palmprint feature illustrated in Fig. 5. Also changes in weight may affect recognition accuracy, e.g. thicker fingers for Shape, see Fig. 6.

Finally, when combining all modalities based on weighted sum score fusion (using weights inverse proportional to corresponding feature's EERs ceiled to 0.5%) perfect separation can be achieved for also aged templates.

5 Conclusion

For hand-based features ageing has been shown to decrease accuracy with least impact on Eigenhand, Length and Silhouette. Ageing caused the Minutiae feature with perfect separation for both intra-session experiments to exhibit an EER of 0.63%. While the latter two features exhibit rather high error rates, Eigenhand with 1.22% EER turned out to be rather stable under ageing effects. Fusion has been shown to be able to target ageing issues, with features exhibiting different ageing goats. In the future, age-adaptive fusion techniques should be investigated. Furthermore, the authors plan to relate ageing effects to biometric quality issues to isolate long-term ageing-effects from short-term variation.

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