Template Ageing in non-minutiae Fingerprint Recognition

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***Abstract*—This study uses non-minutiae fingerprint recognition methods to confirm earlier results on the existence of fingerprint template ageing. We performed the experiments on datasets including a time-span of 4 years. The acquisition was performed by using three different commercial off-the-shelf optical fingerprint sensors. Furthermore, we compared the results of those non-minutiae experiments to investigations performed by a traditional minutiae based approach. The analysis exhibits that there are very similar effects in terms of fingerprint template ageing detectable for all considered recognition methods.**

I. Introduction

Over the past decade different fingerprint (FP) recognition methods have been developed. The most typical method employs a feature-based imprint matching. The corresponding features are minutiae points, which are extracted from the FP images and used during the matching step of common recognition systems. In most of the cases those minutiae based methods are outperforming non-minutiae applications. However, according to a few studies there are situations where non-minutiae methods lead to better results compared to the typical minutiae based approaches. It seems that especially on data exhibiting a difficult quality setting (e.g. high amount of distortion due to different acquisition conditions) non-minutiae FP recognition systems sometimes display a better performance in terms of Equal Error Rate (EER) and other measures. This seems plausible as a certain minimal quality is definitely required to detect (and classify) minutiae, while more coarse grained features might still be present even in rather poor quality data.

The aspect of processing imprints characterised by low quality was part of an investigation concerning the development of a phase-based FP recognition system [1]. The authors of this particular study wanted to design a non-minutiae recognition system, which outperforms results of a minutiae-based approach for low quality FP images. Furthermore, in [2] the StirMark-Toolkit was used to perform experiments on the robustness of FP matching. Two non-minutiae fingerprint recognition methods (Fingercode (FC) and Phase-Only-Correlation (POC)) were applied on Fingerprint-Verification-Contest 2004 (FVC2004) datasets, distorted by the StirMark-Toolkit, and better results could be observed compared to the NIST Biometric Image Software (NBIS) for certain distortion conditions, especially for very poor quality. The same non-minutiae recognition systems have been used to run experiments on partly encrypted FVC2004 datasets as well [3]. Both FC and POC exhibit a better performance on those datasets than obtained by the NBIS system. These results call for the application of non-minutiae methods on other difficult datasets, e.g., including a time separation.

This study is not the first one which is using FC and POC on time separated FP data. There is one single previous study so far [4], conducted on data (covering a time-span of 4 years) acquired by off-the-shelf commercial FP scanners employing FC and POC FP recognition. The so-called "Doddington Zoo" concept was used for analysis and observed results confirm the presence of FP template ageing in terms of certain user dependent characteristics. Similar Doddington Zoo-related analysis on time separated data have been conducted in [5], which describes the effects of FP template ageing on a hand-print data base (acquired by a flatbed scanner) covering a time-span of 5 years. The statement "Short-term goats extend to long-term goats" derived from the hand-print data [5] could not be confirmed based on the data in [4]. However, severe FP template ageing effects have been observed on the hand-print data, i.e. a 2-4 times lowered EER performance was stated caused by a 33% decreased amount of genuine comparison scores.

In general, the aspect of FP ageing has been a topic in research since Galton's study on the permanence of human fingerprints (FPs) [6]. Currently there are various methods to measure human skin and corresponding ageing influences. The most important are high-frequency skin ultrasonography, prophilometry, and skin micro-relief descriptors [7]. In particular, FP ageing results in loss of collagen [8], a structural protein responsible for assuring that the human fibrous tissue of the skin remains resilient. Furthermore, various skin diseases influence the FP recognition as well [9].

The aspect of FP template ageing in particular has been considered in a surprisingly low number of studies (apart from [4], [5]) so far. In [10] a recognition accuracy degradation has been found for forensic FP data from the German federal criminal police office (BKA), investigating time intervals of 10 to 30 years. The usage of an 3D finger range dataset, covering a far smaller time-span of 16 weeks, revealed a matching and recognition performance degradation [11] as well.

Another, more recent study [12] detects a decrease of genuine scores for different time-spans (up to 7 years) in forensic FP data. The application of a covariate-fit analysis model revealed that the impact of FP image quality seems to be the more model compliant explanation for the observed FP template ageing than subjects' age and the time-span.

Based on these recent results and the knowledge that non-minutiae fingerprint systems might perform differently compared to typical minutiae methods, we conduct the following investigations. First, we aimed at verifying the presence of FP template ageing using the same datasets as in [4] by analysing EER and Receiver Operating Characteristics (ROC). Second, we want to compare the results gained from the non-minutiae experiments to the information which can be obtained from similar studies using a minutiae-based recognition approach.

The rest of this paper is organised as follows: In Section II, the datasets and FP recognition systems employed in the experiments are introduced. Section III describes the experimental setup and the corresponding results and the final Section IV concludes this paper with a discussion on the eventual detected FP template ageing effects.

II. Datasets and Recognition Systems

The used datasets are provided by the Center for Biometrics and Security Research (CBSR) at the Chinese Academy of Sciences, Institute of Automation (CASIA). The experiments are applied on two different types of datasets. The first one, called "CASIA 2009", is a subset of the publicly available CASIA-FPV5[1] database. It contains 980 FP images of 49 volunteers (both forefinger and second finger) and 5 images of each finger. The acquisition was done by the use of an U.are.U 4000 scanner, produced by DigitalPersona. This optical scanner produces images with a resolution of 512 dots per inch (dpi). The second dataset is called "CASIA 2013". It includes 5 different subsets of FP images acquired in 2013. Each subset contains the same amount of FP images of the same volunteers as described before. The difference between those single subsets is the choice of the FP sensors. In total 3 different sensor types are used. Two datasets have been acquired by an U.are.U 4000 sensor, two by an U.are.U 4500 sensor and one by a TCRU1C sensor. The U.are.U 4500 is closely related to the U.are.U 4000. Due to this fact, the specifications with respect to resolution, image dimensions and bit depth are identical. The third sensor, the TCRU1C, is a capacitive FP sensor. The images are acquired with a resolution of 508 dots per inch (dpi).

In this study three different FP recognition systems have been applied to the data. Two of them are non-minutiae based. The first one is the Fingercode (FC) approach and the second one the Phase-Only-Correlation (POC). Both non-minutiae recognition implementations are based on a custom in-house software including the before referenced algorithms [13]. The minutiae-based recognition software employed is the NIST Biometric Image Software (NBIS)[2].

Fingercode (FC): The first non-minutiae FP recognition system is based on a ridge feature approach. In total a set of 8 Gabor filters (including orientations from $0°$ to $180°$) is applied to the imprints. As a result 8 so called "Standard Deviation Maps" are received. Those maps are combined to one single map, the so called Ridge Feature Map (RFM). During the matching step of the recognition software the RFM's local orientation and frequency information of the imprints are compared to each other. This is done by calculating the correlation value of these features in the Fourier space. Using the ITF (Inverse-Fourier-Transformation) the correlation result is mapped back from the Fourier space and weighted based on the overlap between the imprints afterwards. Those weighted ridge feature values of the FP images are compared to each other using the Euclidean distance, resulting in an matching score value. During the correlation values' calculation the imprints are rotated against each other to find the best fitting position. Thus, there is not one single matching score for each pair of FP images, but a list of scores. The final score value is chosen form this list by selecting the lowest value (cf. [14], [15]). The used implementation is representing a best fitting pair of FP images by a value of 125 and a bad fit by a score of 0.

Phase-Only-Correlation (POC): Compared to the other non-minutiae FP recognition system the POC implementation uses a holistic correlation based method. After a set of rotation and displacement alignment operations are applied to the input images, overlapping regions of both FP are selected. To validate the amount of similarity within those regions a modified Phase-Only-Correlation function [16], the so called BLPOC (Band-Limited Phase-Only Correlation) [17] is calculated. Similar to the FC the application of the BLPOC function results in a list of matching score values due to rotation compensation during the calculation process. The final score value between two imprints is set to the maximum value determined from this list. It will be 1 in case a perfect match is found and 0 if the imprints do not share any information.

NIST Biometric Image Software (NBIS): This tool was implemented by the National Institute of Standards and Technology (NIST). In the present study, release 5.0.0 was applied to the data.

III. Experiments and Results

A. Experimental Setup

In the following experiments the datasets' names, introduced in Section II, will be abbreviated. Thus, dataset A describes the first data base, "CASIA 2009". Furthermore, all datasets from "CASIA 2013" will be named with B as first letter and an index. This results in B1 as abbreviation for the TCRU1C sensor dataset. B2 and B3 are the names ot the U.are.U 4000 sensor datasets, respectively. Finally, B4 and B5 denote the datasets acquired with the U.are.U 4500 sensor.

[1]http://biometrics.idealtest.org/dbDetailForUser.do?id=7

[2]http://www.nist.gov/itl/iad/ig/nbis.cfm

According to the fact that the experiments are designed for template ageing investigations, it is necessary that there are also datasets combining the imprints from 2009 and 2013. This leads to 5 datasets including 1960 images. Those in total will be called ”crossed” and the before discussed datasets A, B1-B5 are the ”single” ones. The ”crossed” data bases are abbreviated by the letter C and an index as well: C1 includes the imprints of A and the TCRU1C sensor, B1. C2 and C3 describe the images of A and the U.are.U 4000 sensor FP images, B2 and B3. Finally, C4 and C5 result from combining A and the remaining U.are.U 4500 sensor imprints, B4 and B5.

The determination of FC, POC and NBIS recognition performance in terms of their matching accuracy is done by calculating a set of 5 commonly used performance figures. Those figures are the EER as mentioned in Section I mentioned EER, measured in percent, the Average Genuine Score (AGS) and Average Impostor Score (AIS) together with the lowest False Rejection Rate (FRR) for False Acceptance Rate (FAR) less or equal to 0.1% (FAR_{100}), and finally the Zero False Acceptance Rate (ZeroFAR). Each of those values has been calculated for all introduced datasets A, B1-B5 and C1-C5.

The corresponding matching scores are obtained by applying the protocol used in all four FP Verification Contests (FVC) (e.g. [18]). As a consequence of the size of the datasets discussed in the preceeding section, there is a different amount of fingerprint images in the ”single” and ”crossed” datasets. Performing the matching score calculation, following the FVC protocol, it is obvious that a different number genuine and impostor scores will be obtained. In total, 1960 genuine and 95550 impostor matches were computed for the ”single” datasets. The “crossed” datasets’ number of genuine and impostor matches is 4.5 times and 4 times as high as that of datasets A and B1-B5, respectively. This imbalance might question a direct comparison of the performance figures between “single” and “crossed” datasets. In order to equalise the number of matching scores, a randomised selection strategy of the “crossed” scores was applied. This random selection of 1960 genuine and 95550 impostor matches was repeated $\binom{10}{5}$ times and the obtained accuracy values were averaged afterwards.

B. Results: FC and POC Experiments

In the following result Tables I - V and VIII the best EER values are highlighted in bold. At first we will discuss the results displayed in Tables I - IV. The second part of the analysis focuses on the comparison between those values and the minutiae-based performance figures.

Table I and II show the results for experiments including all possible genuine and impostor matches. The randomised selection of the matching scores was considered in a set of additional experiments (see Tables III and IV).

In general it seems that the overall performance of FC and POC is not very good because the EER values are much higher than expected. The only exception can be observed in Table II considering the results for B1 - B5. Those values are comparable to previous results using these methods (e.g. [13]). Apart from this first impression an interesting trend can be observed. There is a clear increase of EER, FAR_{100} and ZeroFAR when comparing results from single and crossed datasets. Furthermore, when considering the AGS and AIS values the increase of the other 3 measures for the crossed sets is logical. In case of the genuine scores a clear reduction of the values for datasets C1 - C5 is present, while the impostor scores are remarkably stable. Those observations can be made in both, FC and POC results, independently.

Tab. I: Performance values of FC matching for all datasets using all matches.

dataset	**EER** (%)	**AGS**	**AIS**	**FAR_{100}**	**ZeroFAR**
single					
A	23.86	110.24	102.03	0.53	0.84
$B1$	17.13	113.18	104.62	0.37	0.66
$B2$	12.20	113.10	104.67	0.33	0.66
$B3$	17.32	111.06	103.50	0.41	0.74
$B4$	**11.72**	112.56	102.80	0.26	0.71
$B5$	16.73	111.11	102.21	0.38	0.97
crossed					
$C1$	**20.15**	112.81	102.13	0.43	0.69
$C2$	27.23	108.72	102.67	0.65	0.92
$C3$	25.70	108.52	102.44	0.65	0.94
$C4$	25.66	108.62	102.19	0.63	0.92
$C5$	27.21	108.12	102.00	0.65	0.99

Tab. II: Performance values of POC matching for all datasets using all matches.

dataset	**EER** (%)	**AGS**	**AIS**	**FAR_{100}**	**ZeroFAR**
single					
A	25.39	0.24	0.11	0.44	0.77
$B1$	11.67	0.30	0.11	0.20	0.70
$B2$	8.00	0.31	0.11	0.15	0.57
$B3$	10.90	0.30	0.11	0.19	0.53
$B4$	**6.87**	0.35	0.11	0.11	0.64
$B5$	10.04	0.31	0.11	0.20	0.73
crossed					
$C1$	37.75	0.18	0.11	0.69	0.89
$C2$	27.58	0.21	0.11	0.52	0.85
$C3$	26.12	0.21	0.11	0.50	0.85
$C4$	**24.62**	0.23	0.11	0.47	0.88
$C5$	25.63	0.21	0.11	0.49	0.90

Tab. III: Randomised score selection performance values of FC matching for the crossed datasets.

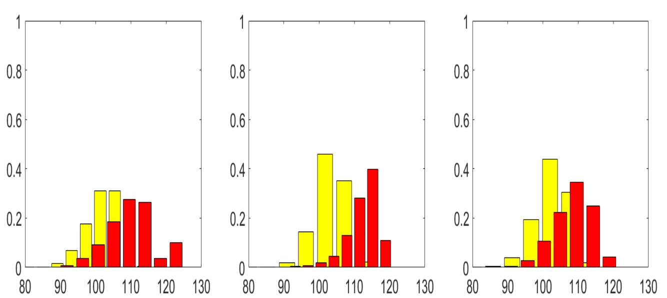
dataset	**EER** (%)	**AGS**	**AIS**	**FAR_{100}**	**ZeroFAR**
	crossed - randomly selected scores				
$C1$	**20.23**	112.81	102.13	0.43	0.67
$C2$	27.24	108.71	102.67	0.65	0.91
$C3$	25.73	108.51	102.44	0.65	0.94
$C4$	25.69	108.62	102.19	0.62	0.91
$C5$	27.20	108.12	102.00	0.65	0.94

In the following we discuss results obtained by the randomised matching score selection as discussed in Section III-A. The corresponding results for FC and POC experiments are listed in Tables III and IV. Considering the performance figures hardly any difference between the “crossed” datasets’ experiments conducted with the full set of matches and those with randomised score selection can be observed. Of course there some small fluctuations which are caused by the underlying “single” datasets. There is only one larger variation affecting the results of C1 applying POC. The experiments using all matches display an EER of about 38% while the randomly score values experiment results in an EER at 25.56%. The relatively large difference is an interesting and unexpected observation that might be attributed to a fortunate random selection of score subsets. However, overall it seems to be reliable to consider the results using all matches in a comparison between single and crossed datasets despite the difference in terms of absolute number of matches involved.

Tab. IV: Randomised score selection performance values of POC matching for the crossed datasets.

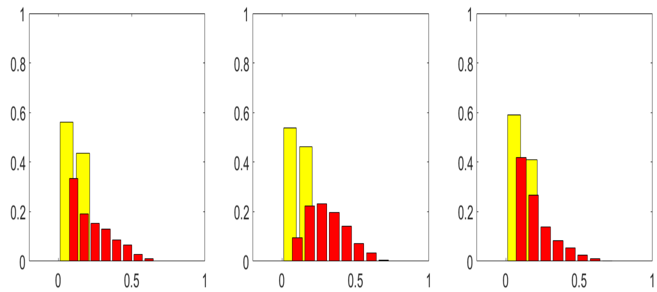
dataset	**EER** (%)	**AGS**	**AIS**	**FAR$_{100}$**	**ZeroFAR**
	crossed - randomly selected scores				
$C1$	25.56	0.21	0.11	0.51	0.83
$C2$	27.66	0.21	0.11	0.53	0.83
$C3$	26.13	0.21	0.11	0.50	0.82
$C4$	**24.57**	0.23	0.11	0.47	0.83
$C5$	25.63	0.21	0.11	0.49	0.86

Summarising these first results we conclude that according to the decrease of the AGS and the stability of AIS values for time separated (i.e. crossed) data in combination with the increase of the EER and other measures that we are indeed confronted with FP template ageing.
In the following Figures 1 and 2 this trend can be confirmed visually as well by visualising actual genuine and impostor score distributions, respectively. The datasets for the examples have been chosen randomly because effects do not differ among the different datasets. For both examples (FC and POC), the amount of genuine scores (colored red) with low matching values in the rightmost chart (c) (corresponding to C4 or C3) is much higher as compared to the cases of the “single” datasets as shown in charts (a) and (b). On the other hand, no actual difference in the impostor score distribution (colored yellow) among single and crossed datasets is visible. This clear shift of the genuine score distribution to the left confirms earlier findings in FP ageing-related investigations (e.g. [5], [12]). Thus, a confirmation of FP template ageing effects, based on non-minutiae recognition schemes and their templates, can be clearly stated.



(a) Set A (b) Set B4 (c) Set C4

Fig. 1: Genuine (colored red) and Impostor (colored yellow) score distribution of the FC A, B4 and C4 data set.



(a) Set A (b) Set B3 (c) Set C3

Fig. 2: Genuine (colored red) and Impostor (colored yellow) score distribution of the POC A, B2 and C2 data set.

C. NBIS Experiments

After performing the FC and POC experiments, the same experimental setup was used to repeat the investigations applying the NBIS recognition system to the data. We want to verify if the observed template ageing effect also translates to minutiae-based recognition. Thus, this study is the first one, applying both non-minutiae and minutiae-based recognition schemes to the same time separated datasets.
Table V presents the same performance measures corresponding to all computed matches as in Table I and II.

Tab. V: Performance values of NBIS matching for all datasets using all matches.

dataset	**EER**	**AGS**	**AIS**	**FAR$_{100}$**	**ZeroFAR**
single					
A	7.42	64.03	6.78	0.13	0.34
$B1$	8.95	64.87	6.64	0.15	0.39
$B2$	8.17	64.63	6.53	0.13	0.35
$B3$	9.07	53.69	6.83	0.18	0.81
$B4$	**5.96**	70.56	6.37	0.10	0.91
$B5$	7.30	67.30	6.34	0.14	0.97
crossed					
$C1$	**12.63**	47.61	6.58	0.26	0.57
$C2$	14.76	44.71	6.51	0.29	0.58
$C3$	14.37	43.81	6.71	0.29	0.87
$C4$	13.18	49.06	6.52	0.25	0.97
$C5$	13.46	48.65	6.50	0.25	0.99

First, the overall performance of the NBIS system is much better compared to previous FC and POC results (e.g. the EER is reduced to half the size for most datasets). This leads to an interesting question concerning the quality of the imprints. As usually FC and POC are superior to NBIS only for very low quality datasets, it can be assumed that the quality of the used FP images cannot be that low, because otherwise the performance of FC and POC would be better.
To verify this assumption the NIST FP Image Quality (NFIQ)[3] and the non-reference metric “Blind Referenceless Image Spatial Quality Evaluator” (BRISQUE)[4] [19] were applied to the given datasets. The average quality values are displayed in Table VI. For the average NFIQ values’ calculation a weighted

[3]http://www.nist.gov/itl/iad/ig/nigos.cfm#Releases
[4]http://live.ece.utexas.edu/research/Quality/index.htm

approach as introduced in [20] was applied. If an NFIQ value is close to 0 this indicates lowest possible quality and a value of 100 indicates best quality. For BRISQUE, those values are flipped. A value of 0 can be interpreted as best possible quality and 100 as worst one. The results in Table VI show that the average quality of the datasets is not really good, but not very bad as well. This could serve as an explanation for the low recognition accuracy of the used non minutiae recognition systems as these only outperform minutiae-based ones on very low-quality data. As a comparison, we have computed average NFIQ and BRISQUE values for the three natural FP subsets of the FVC 2004 data (DB1: A, DB2: A, DB3: A) which confirm the observation that the datasets considered in this study are of rather average quality (cf. VII). Despite, it seems that the BRISQUE quality of the used CASIA datasets is slightly better compared to the data bases from FVC2004.

Tab. VI: Average NFIQ and BRISQUE values per CASIA dataset.

datasets	**av. NFIQ value**	**av. BRISQUE value**
A	78.40	49.63
B1	85.33	31.52
B2	65.84	45.28
B3	64.09	44.51
B4	69.73	46.75
B5	73.09	50.14
C1	81.87	40.58
C2	72.12	47.46
C3	71.25	47.07
C4	74.06	48.19
C5	75.75	49.89

Tab. VII: Average NFIQ and BRISQUE values per FVC2004 dataset.

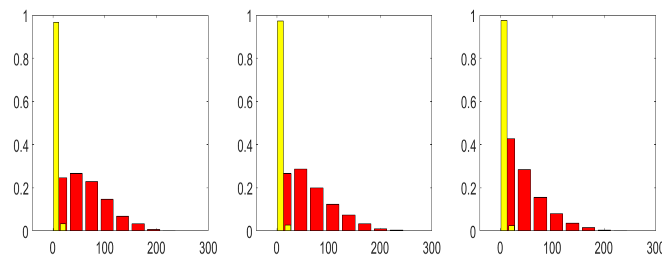
datasets	**av. NFIQ value**	**av. BRISQUE value**
DB1**: A**	98.15	53.30
DB2**: A**	88.05	57.43
DB3**: A**	95.08	57.07

Apart from the overall much better recognition accuracy, we observe identical template ageing effects in the NBIS performance figures as seen in FC and POC results, respectively. The EER, FAR_{100} and ZeroFAR are much higher in datasets C1-C5 compared to A, B1 - B5. The AGS is also decreased and the AIS remains almost stable also in the NBIS data. Thus, also NBIS data exhibits an analogous template ageing effect.

Tab. VIII: Randomised score selection performance values of NBIS matching for the crossed datasets.

dataset	**EER**	**AGS**	**AIS**	**FAR**$_{100}$	**ZeroFAR**
	crossed - randomly selected scores				
$C1$	**12.82**	47.56	6.58	0.26	0.53
$C2$	14.79	44.69	6.51	0.29	0.57
$C3$	14.10	43.84	6.71	0.29	0.75
$C4$	13.15	49.07	6.52	0.25	0.60
$C5$	13.38	48.74	6.50	0.25	0.71

By analogy to the FC and POC case, there is also no difference between the performance figures obtained when using random score selection (leading to a balanced number of matching scores in single and crossed datasets) and the usage of all matching scores in the crossed sets (cf. Table VIII). The graphical representation (see Figure 3) of the A, B1 and C1 NBIS matching score distributions emphasises the identical trend as seen on FC and POC score distributions as well. Similar to Figures 1 and 2 the x-axis describes the matching scores and the y-axis the percentage of matches within a bin (scaled from 0 to 1). In fact, the shift of the genuine score distribution is even clearer in Figure 3 (NBIS score data) compared to earlier Figures 1 (FC) and 2 (POC).



(a) Set A (b) Set B2 (c) Set C2

Fig. 3: Genuine (colored red) and Impostor (colored yellow) score distribution of NBIS A, B1 and C1 dataset.

IV. Conclusion

Fingerprint template ageing effects have been demonstrated for different types of datasets (e.g. forensic data [12], [21], data acquired by a flatbed scanner [5], and data acquired with different types of off-the-shelf commercial FP readers [22]). However, all these investigations have employed either minutiae-based FP recognition schemes [12], [21], [5] or are not based on the classical EER / ROC based recognition performance assessment [22].

In this work we were able to show FP template ageing effects using two non-minutiae type FP recognition schemes (i.e. clearly worsened EER and ROC performance figures for time-separated data) and confirmed these effects also using the popular minutiae-based NBIS FP matching scheme. Thus, for the data considered, template ageing is present for three very different types of FP matching schemes and one might eventually conjecture that it is present independent of the employed FP recognition scheme. Still, more types of FP recogniiton schemes will be considered in future work.

However, the reason for the observed phenomena can only be subject to speculation as we have not tackled this question so far regarding the datasets in question. Possible reasons include differing fingerprint quality in the data acquired at distinct points in time (as identified in [12] as cause in their dataset), differing non-quality related acquisition conditions, subject ageing (and thus skin ageing) effects, and many others. This important issue is also subject to further investigations.

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