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Fingerprint Template Ageing vs. Template Changes Revisited

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***Abstract*—This study investigates the impact of "ghost" fingerprint and minutiae information in 4 year time-span separated fingerprint datasets. A high amount of ghost fingerprints within the data, eventually a source for differences in acquisition conditions, might be responsible for recently reported template ageing effects. According to that, various experiments have been performed to get rid of this problematic image content and to compare the corresponding matching results to the performance figures using the non altered imprints. The analysis with respect to detected increased error rates exhibits very similar effects for all considered methods no matter if ghost fingerprint information is removed or not. Thus, ghost fingerprints are not responsible for the observed effects.**

I. INTRODUCTION

The ISO/IEC biometric testing standard ISO/IEC 19795-1 reports that "Longer time intervals generally make it more difficult to match samples to templates due to the phenomenon known as template ageing" [1]. The standard then defines "template-ageing" as an "increase in error rates caused by time-related changes in the biometric pattern, its presentation, and the sensor". Apart from time-related changes various other reasons can cause performance degradations in fingerprint (FP) recognition as well. The most prominent ones are the usage of different sensors and sensor types, alternation in ambient conditions (e.g. changes in the illumination set-up), differences in the acquisition protocol like variability in sensor plates' cleaning, weather conditions, or various skin diseases as reported in [2].

Considering the high number of potential reasons for FP recognition accuracy degradations, we investigate a different (i.e. not time-related) explanation for the recently postulated template ageing effects on time separated data [3], [4] in this work. In [5] it is confirmed that a) FP images can be designed which include the biometric minutiae information of at least 2 fingers and b) that such imprints cause serious troubles during the recognition process using state-of-the-art implementations. In Figure 2, displaying example imprints of the datasets used in [3], [4], it is easy to find minutiae information in the background, which clearly do not belong to the acquired finger in the region of interest (ROI). This additional information, a so called "ghost" FP, can be found very frequently in the considered datasets. It is rather obvious that a ghost FP would not cause any decrease in the quality measure analysis as performed in [3], [4]. Further, the presence of ghost FP was discussed as a complicating factor during FP segmentation in [6]–[8] and most importantly, the detailed observation of our considered imprints revealed that background information (i.e. ghost FP) is not always present in each image of the used data. There are images which contain identical ghost FPs each time an imprint of the same finger is acquired. But, there are also FP images available where no such information can be retrieved. This alteration in the presence of ghost FPs actually leads to template changes, which could cause changing error rates and thus could be made responsible for template ageing effects. However, it is not correct that these changes can be classified as being time-related. A varying presence of ghost FPs is caused by acquisition protocol variations, i.e. the definition when the sensor surface is being cleaned. Of course, acquisition protocols differing with respect to this property could be used in two sessions without any time separation in-between. Thus, if our experiments reveal that ghost FPs cause the observed effects, template ageing is not the reason but a time-unrelated template change effect.

The rest of this paper is organised as follows: In Section 2, we review the current state of the art on the relation of fingerprint recognition and ageing. The experimental setup, i.e. the used FP recognition SDKs, datasets and a detailed discussion on the used experimental methodology will be presented in Section 3. The subsequently performed experiments and corresponding results are analysed in Section 4, before concluding this study in Section 5.

II. FINGERPRINT RECOGNITION AND AGEING

The biological reason for FP ageing is the loss of collagen [9]. This structural protein ensures that the human skins' fibrous tissue is resilient during time. Even though, it is possible to measure skin ageing. The most prominent methods are the usage of high-frequency skin ultrasonography, prophilometry and skin micro-relief descriptors [10]. Furthermore it is even possible to describe skin topography changes from capacity images by analysing the 3D profile. This analysis reveals the introduction of wrinkles and a cell enlargement caused by the biological ageing process [11]. Uchida et al. [12] quantify skin ageing by analysing 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. But there are also more recent studies which focus on the ageing behaviour of latent FP, being of high importance in crime scene analysis, looking into biological aspects in more detail. First the FP information of the various test subjects was deposited at e.g. glass or synthetic material. The particular biometric traits were acquired after some period exhibiting different time-spans. In [13] the relationship of these latent FPs, their corresponding time-spans and biological degradations during the specified time period was investigated. Apart from classical examination methods like morphological and structural approaches, biochemical and DNA based tests have been used as well to measure FP degradations. The investigations revealed that for example the blood groups do have an influence on the degradation. It seems that people exhibiting blood group B are slightly more resistant to biochemical ageing influences. Of course those results are more important for forensic datasets, but small biochemical variations could also lead to degradations which can influence the recognition process. The authors of this particular study used 800 FP images for the performed experiments. Further specifications on the used analysis tools, e.g. microscope and DNA extraction process, may be looked up in [13].

Another biological aspect was investigated in [14], using chromatic white light sensors to study latent long-term FP ageing. The authors state that an image contrast loss can be observed over time, considering imprints of 40 volunteers. The corresponding images have been acquired at three different locations independently and were compared during the experiments based on four different research goals. The results revealed a high number of variance among the different time series of user's FP images. The authors concluded that the reason for this observation might be a different biochemical composition of the imprints.

A. Fingerprint Age Group Analysis

Focusing on the aspect of human ageing it is natural that studies have been performed, which investigate the influence of different subject age groups in FP datasets on recognition performance. In [15] it was shown that older age groups exhibit a worse performance in terms of FP quality and recognition performance. This conclusion was achieved by analysing the relationship between FP's moisture content and the volunteer's age using a one-way analysis of variance (ANOVA) and the Pearson correlation coefficient. The corresponding database contains images of 79 people (age group from 18-25) and imprints of 60 people (age group 62+). In total 948 images of age group 18-25 and 720 of the second age group are included in this dataset. Of each volunteer, 3 images of each index finger (left and right hand) have been acquired. This database was reused in subsequent research [16], where the authors focused on minutiae point based analysis. This resulted in the conclusion that elderly people exhibit a higher number of minutiae points, but the biometric quality (using NIST Fingerprint Image Quality algorithm[1]) displayed a degradation compared to the younger age group. Finally in [9] this investigation was extended once more. The dataset was expanded by two additional age groups (26-39 and 40-64). The authors could confirm the results stated by [15] that older age groups are displaying a worse performance in terms of FP quality and recognition.

In [17] a similar study was performed, but the core aspect of this research was the consideration of a different dataset exhibiting very young people as well. Not only age groups of volunteers older than 19 years have been taken into account, but also the age group from 3 to 18 years. According to this aspect two different sub-datasets have been acquired: One containing the adult biometric templates (172 in total) and one displaying the young volunteers' images (498 in total). Further specific information on the volunteers can be looked up in [17]. Additionally it must be mentioned that the acquisition was done by the use of a optical scanning device (a HP 3500c flatbed scanner) with 500 dpi resolution, capturing the full hand. Data analysis was done by the usage of 5 different (hand-)geometric and texture-based methodologies, including FP minutiae, eigenfingers, geometric and shape based approaches. The interested reader is referred to [18] (eigenfingers) and [19] (geometric methods) for more detailed information on those techniques.

The final results concerning the recognition performance are based on three different age groups. These groups have been selected as subsets of the previously introduced adult and children datasets: The first group is called young group and contains all images of children who are between 3 and 10 years old, the second one (youth group) includes the imprints of all volunteers whose age is between 11 and 18 years, and finally the adult group (19+ years). In most performed experiments it can be observed that kids' FP performance suffers compared to adults recognition performance [17].

To cope with different age groups and effects which are introduced by the usage of data exhibiting such variability some studies have been performed as well. In [20] an isotropic rescaling method was used on children data to improve the recognition performance from $11-14\%$ to $5-6\%$ equal error rate (EER). The experiments were done on imprints, whose feature extraction and matching procedure was improved by analysing the FP's shape and the application of some rescaling approach.

B. Fingerprint Ageing Analysis (FP Template Ageing)

Ageing effects in human FP recognition been a topic in research since Galton's first study on the permanence of FPs [21]. In all papers discussed subsequently, increased error rates have been reported for time-separated data. Time intervals of 10 to 30 years have been studied in [22] using a dataset provided by the German federal criminal police office (BKA, i.e. forensic FPs). The authors reported a lower recognition

[1]https://www.nist.gov/programs-projects/biometric-quality-homepage

accuracy when the time interval is increased. Further, [23] performed experiments on the so called Korea Fingerprint Recognition Interoperability Alliance (KFRIA) database acquired with three different commercial sensors (2 optical and 1 capacitive sensor type). This dataset exhibits a time span of 1 year between acquisition sessions, which is quite a short time gap, but despite this fact the authors have been able to report an EER increase using three different sensors. The EER of the second acquisition's data was about two times higher than the EER of the corresponding imprint of the first acquisition.

Similar to these results of [22], [23], a degradation of different FP matching performance figures (e.g. equal error rate (EER)) was observed on data acquired by a flatbed scanner [24], where in particular a decrease of genuine scores was detected for a time separation of 5 years (the genuine scores revealed a decrease of roughly 33% and a 2-4 times lowered EER performance is found). These observations were confirmed on a further massive forensic FP dataset including time-spans up to 7 years in [25] as well. Similar to the detected genuine score degradation on 2D FP data discussed so far, it was possible to observe a decrease in matching and recognition performance using some 3D finger range data which were acquired by covering only a time span of 16 weeks between sessions [26]. In [27], the presence of similar effects are confirmed on time-separated FP data acquired by off-the-shelf commercial FP scanners by analysing user-group specific effects which are known as the "Doddington Zoo" concept [28]. Further investigations on the same data [3], [4] revealed very similar effects with respect to decreased recognition performance on time separated data as reported by [24], [25].

However, most studies done on time-separated FP data have not performed experiments to reveal the reasons for decreased recognition accuracy in detail. In fact, it does not suffice to describe increased error rates on time separated data to have observed a template ageing effect. To be compliant with the definition, time-related changes have to introduce the observed effects, while the sole employment of time-separated data does not automatically imply template ageing being present in case of higher errors (as these might be caused by non-time-related changes). Only few of the studies on time-separated FP data [3], [4], [25] try to explain why the observed effects occur. The very extensive covariate-fit analysis model in [25] revealed that differences in image quality explain the observed increased errors better as time-related changes. In [3], [4] the analysis did not indicate that FP biometric quality decrease can be made responsible for the claimed template ageing effects. However, these studies unfortunately did not employ the identical experimental and statistical set-up and thus do not even fully clarify the contribution of FP quality to the observed effects, as the results contradict each other.

A potential generic approach to cope with FP template ageing effects is the usage of template update techniques, which have been investigated for example by [29]. The authors of this particular study used an adaptive feature set introduced by an algorithm allowing to reduce intra-personal variabilities over time. Similar to this approach there is more recent work focusing on self-updating algorithms [30]. The mentioned update methods provide a path-based clustering setup to enhance the initial template selection before starting the update process on the one hand. On the other hand an improved adaption of the recognition system's threshold is ensured as well in case high environmental variability is measured.

III. Experimental Setup

The experiments have been conducted using two minutiae based FP recognition SDKs: the *NIST Biometric Image Software (NBIS)* and the Neurotechnology *VeriFinger SDK (NEURO)*. The first one (release $5.0.0$) has been implemented by the National Institute of Standards and Technology (NIST)[2]. The second recognition approach (release 9.0) was developed by the Lithuanian company Neurotechnology[3].

According to the study purpose we are using datasets already analysed earlier [3], [4], [31]. The data has been acquired at the Center for Biometrics and Security Research (CBSR) at the Chinese Academy of Sciences, Institute of Automation (CASIA) in 2009 and 2013. The imprints from 2009 are a subset of the publicly available CASIA fingerprint database V5[4]. Using an U.are.U 4000 scanner (produced by DigitalPersona), images of both forefingers and second fingers of 49 volunteers are stored in dataset "CASIA 2009", which will be denote by A. In total 980 fingerprint images are available, 5 imprints of each finger. The same acquisition process was repeated four years later to create the "CASIA 2013" database, which includes 5 independent subsets in total. Each subset contains again 980 images of the same volunteers. The main difference among the subsets is the usage of various sensors, among them optical and capacitive fingerprint sensors. They are denoted as $B1$-$B5$. Apart from the "single" datasets containing only imprints of 2009 or 2013 independently, it was necessary to combine the imprints of both years to get so called "crossed", i.e. time-separated, datasets $C1$-$C5$. In each of these crossed sets the imprints from 2009 and one of the 2013 "single" datasets are combined (e.g. C1 contains the imprints of A and B1). Further information on the concrete specifications can be found in [3], [4], [31]. For all recognition experiments and datasets the same performance figures as in [3] have been derived to evaluate the recognition results. For the evaluation process of the recognition accuracy, the Fingerprint Verification Contests' (FVC) procedure was performed, see [32].

In the following, we describe the different techniques applied to separate (minutiae) data resulting from the currently acquired FP and the already present ghost FP.

Masking the Background (MBw): This first method is used to separate the background and region of interest (ROI) of the FP images from each other by applying FP

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

[3]http://www.neurotechnology.com/verifinger.html

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

segmentation. After sharpening the edge information we used a Sobel operator to retrieve the edges of the ROI. We also tested other edge detection algorithms (e.g. Canny Edge detector, Prewitt operator and Harris corner points as used in [7]), but for the given data, the Sobel approach worked best. Subsequently performing image dilation and erosion calculations we obtained the final masks. In Figures 1a) and b) an imprint mask and the combination of mask and image is displayed.

Smooth Masking of the Background (SMB): This approach was designed to enhance the background masking method (MBw). According to the fact that the edges of the masks could introduce new positions where minutiae information may be detected falsely, a Gaussian smoothing operation using $\sigma = 2$ as parameter was applied. In Figures 1c) and d) the example image of user 7 can be seen.

Splitting the ROI and Background minutiae (ROIm): This method was designed to perform a reference analysis for the background masking method in order to mitigate for newly created minutiae caused by the masking operation. For that reason we created the minutiae files, then we used the background masks to separate the minutiae which have been detected in the background and in the ROI. The selected minutiae were stored in two single files and we repeated the matching process using NBIS on the background and the ROI minutiae independently. Results are provided for the ROI minutiae only, as background minutiae do not lead to sensible recognition results.

Removing "stable" ROI and Background minutiae (wS and ROIwS): The previously introduced approaches are focusing on removing artifacts caused by ghost FPs by focusing on the ROI only - spatial background information is removed. However, ghost FP might also affect the ROI of course. To discriminate minutiae resulting from ghost FP from minutiae of the current imprint, we introduce the concept of "stable minutiae". While for taking different imprints of the same finger the finger is lifted off the sensor and re-allocated each time the data is acquired (causing the FP minutiae to manifest at different spatial locations), this is not the case for minutiae caused by ghost FPs, as these are detectable at the same x- and y- axis position (as long as the sensor is not cleaned minutiae information of some previous acquisition of the same finger remained on the sensor plate). According to a visual analysis it could be confirmed that there is FP information of the same finger from a previous acquisition present in most of the cases (see Figure 2 as example). In the presented images minutiae in the ROI are coloured red and blue if they belong to the background. If a minutia is marked as stable it is coloured green (ROI) or magenta (background).

FP recognition, using NBIS minutiae files without stable features (these are explicitly removed), was performed in two different ways. For the first case, we removed the stable minutiae information in the entire minutiae files. This led to results using all the minutiae detectable in the whole images, except the removed stable ones. We abbreviated this method with "wS" as acronym for "withoutStable". In the second approach we only focused on the ROI area for recognition and removed the stable minutiae there. The corresponding abbreviation is "ROIwS".

In Table I the number of images where stable minutiae information can be detected is presented in column *all images* (together with the relative amount of images in percent). In columns *all minutiae*, *ROIm* and *ROIwS* the average number of detected minutiae is displayed as well as the standard deviation concerning the minutiae appearance in the selected methods. In column *ROIm* the results considering only minutiae within the ROI exhibit a clear difference compared to using the whole imprints. According to the fact that ghost FPs are present in nearly all images of the datasets it is understandable why the mean values in *ROIm* are lower as in the *all minutiae* case. In terms of the standard deviation only minor fluctuations can be observed. The same minor variations can be detected in *ROIwS*. It seems that stable features are rarely in the imprints' ROI, which could be a disproof of the assumption that stable minutiae are responsible for effects exhibiting higher errors. Nevertheless, we considered this set-up in the recognition process as well because we wanted to prove/disprove the statement entirely.

IV. Experimental Evaluation

The most important results (the EER values for the different experimental set-ups) are presented in Table II. In the first two columns the reference results, which have been calculated by analogy to [3], are displayed. The differences in NEURO results as compared to the original ones of [3] are caused by the usage of different SDK releases. The following columns represent the various experimental outcomes we obtained in this study. The best results are highlighted in bold numbers. The most obvious observation using NBIS is that the method MBw leads to a clearly worse EER performance compared to the reference values. This fact is not only valid for the single datasets, but also for the crossed ones in all cases. Further, the removal of ghost FPs does enhance the performance if it is done in a smooth way using some Gaussian filtering (SMB) because comparable measures can be reported for that case independently from NBIS and NEURO. Additionally, it is observable that the removal of stable features as it is done in wS and ROIwS experiments hardly influences the performance. According to that it can be concluded that the experiments we performed in removing ghost FPs did not have any impact on the higher error rates for time separated data in case of the EER. This performance figure is much higher for the time-separated datasets once more. But, the de-masking of ghost FPs does have an impact on the EER if it is done in a very rough way because new minutiae are introduced falsely (see MBw vs. SMB results). We also performed FP recognition using only the background information for all the described methods, but it was not possible to get EER values below (49%). Apart from that, it is interesting to observe that the

(a) Imprint mask. (b) Mask and image combined. (c) Imprint smooth mask. (d) Smooth mask and image combined.

Fig. 1: Background masked fingerprint images of user 7, dataset $B4$.

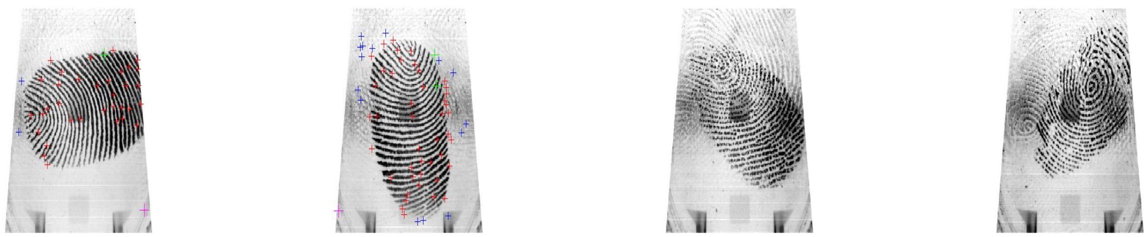


Fig. 2: Images with "stable" minutiae (first two images from the left) and ghost fingerprints.

Tab. I: Number of images with "stable" minutiae and minutiae counts of all detectable minutiae.

dataset	*all images*	*all minutiae*		*ROIm*		*ROIwS*	
		μ	σ	μ	σ	μ	σ
A	504 (51.43%)	59.98	15.56	46.61	13.21	46.31	13.15
$B1$	180 (18.36%)	56.05	19.62	52.86	18.43	52.02	18.48
$B2$	364 (37.14%)	59.42	18.90	47.14	16.14	46.72	16.06
$B3$	500 (51.02%)	69.17	19.28	52.43	17.16	52.02	17.11
$B4$	416 (42.44%)	69.56	21.89	56.31	20.27	55.82	20.19
$B5$	246 (25.10%)	64.57	25.17	59.78	25.18	59.04	25.16

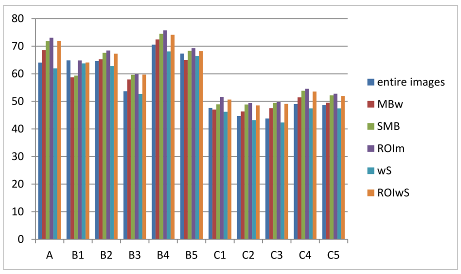
usage of NEURO on dataset $C1$ indicates extraordinary cross-sensor effects, which have not been reported in [3]. This must be caused by the different release we used. In the following we are going to discuss the other performance figures: Average Genuine Scores (AGS), Average Impostor Scores (AIS), the lowest FRR for FAR less or equal to 0.1% (FAR_{100}), and Zero False Acceptance Rate (ZeroFAR). The results can be looked up in Figure 3. At first we want to discuss the most important observation concerning a possible template ageing effect based on the AGS values: The decrease in the genuine scores is detectable for all performed NBIS and NEURO experiments independently. This is observable in Figures 3a) and b). There are fluctuations depending on the used dataset and analysis method, but the overall trend is similar. It is confirmed that NEURO exhibits some cross-sensor effects in dataset $C1$ because comparing images of the same finger involving the time-span leads to much lower genuine scores as can be seen by matching images of the same year. According to that the AGS for $C1$ is much lower compared to all the other datasets. For the average impostor scores (AIS) (see Figures 3c) and d)) a very similar stable behaviour as detected in [3] can be described for the NBIS system. In case of NEURO there are some dataset dependent fluctuations which are based on the used datasets. In general it is interesting to observe that the crossed datasets' AIS is lower as in the single datasets from 2013. The experiments' FAR_{100} can be looked up in Figures 3e) and f). For both recognition methods it can be reported that the FAR_{100} is higher in all crossed datasets. Using NBIS the MB's performance figure is always worse compared to the others and some minor fluctuations can be detected for the other analysis methods. The high amount of variation is not describable in the NEURO case. Finally, we are having a look at the ZeroFAR values which are displayed in Figures 3g) and h). In general, the ZeroFAR for the crossed cases is always higher as for the single datasets. Nevertheless it must be mentioned that especially the results of $B3$-$B5$ and $C3$-$C5$ are much higher compared to the remaining values of the other datasets.

V. Conclusion

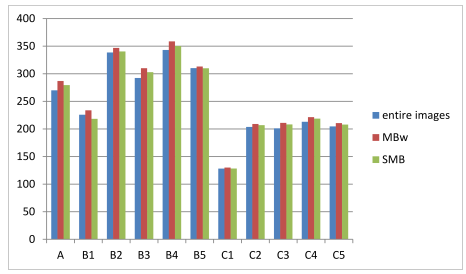
Based on the fact that in the given data a high number of ghost FPs (and thus stable minutiae) can be reported, it was a likely assumption that these might be responsible for the EER increase and average genuine score decrease in FP images exhibiting a time-span of 4 years. According to the knowledge that ghost FPs cause problems in FP segmentation (see [6]–[8]) and that double biometric identities influence the recognition process (see [5]) the erroneous ghost FP information was removed using various methods. However, the same tendencies with respect to higher error rates, in particular increased EER and FRR caused by decreased

Tab. II: EER results of all datasets using NBIS and NEURO.

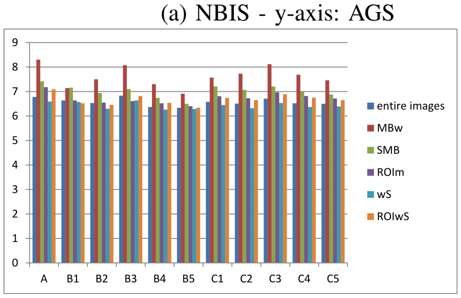
dataset	**entire images**		**MBw**		**SMB**		**ROIm**	**wS**	**ROIwS**
	NBIS	*NEURO*	*NBIS*	*NEURO*	*NBIS*	*NEURO*	*NBIS*	*NBIS*	*NBIS*
	single - all matching scores								
A	7.42	1.58	9.94	2.42	7.47	1.59	7.63	7.45	7.67
$B1$	8.95	2.77	10.98	2.84	9.71	2.58	8.98	8.93	9.09
$B2$	8.17	0.74	9.07	0.91	7.78	**0.66**	7.64	8.17	8.50
$B3$	9.07	3.06	11.68	3.34	8.99	3.03	9.40	9.24	9.35
$B4$	5.96	0.99	6.82	1.01	6.34	1.04	**5.70**	6.18	5.81
$B5$	7.30	1.29	9.65	1.61	7.82	1.42	7.59	8.23	7.53
	crossed - all matching scores								
$C1$	**12.63**	21.09	15.56	21.61	14.09	21.21	13.15	14.01	13.15
$C2$	14.76	4.55	17.79	5.02	14.99	4.42	14.43	14.85	14.46
$C3$	14.37	4.61	17.24	4.63	14.42	4.43	13.77	14.43	13.74
$C4$	13.18	**3.83**	15.66	4.10	13.35	3.93	12.94	13.26	12.97
$C5$	13.46	4.61	16.66	4.78	13.48	4.53	12.86	13.51	12.86



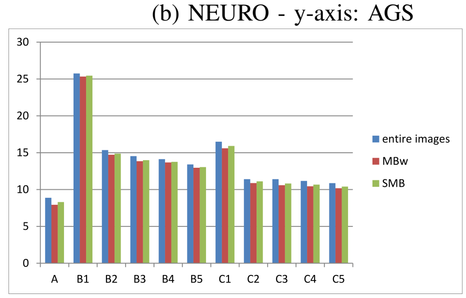
(a) NBIS - y-axis: AGS



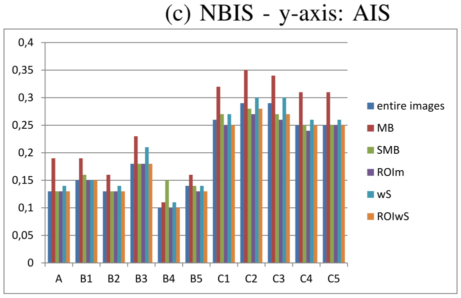
(b) NEURO - y-axis: AGS



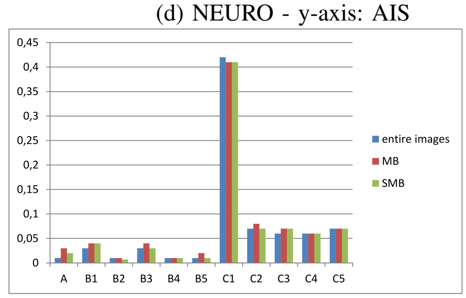
(c) NBIS - y-axis: AIS



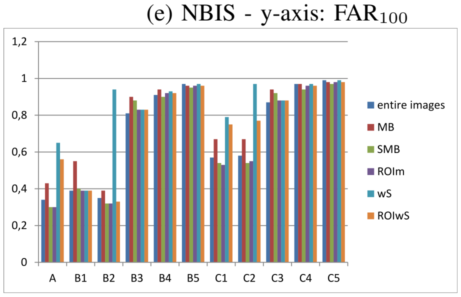
(d) NEURO - y-axis: AIS



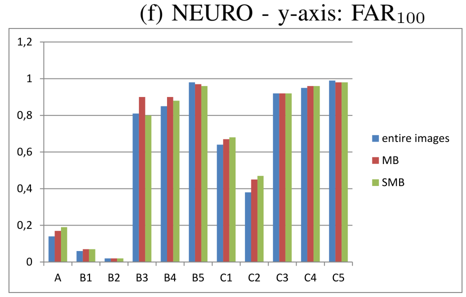
(e) NBIS - y-axis: FAR_{100}



(f) NEURO - y-axis: FAR_{100}



(g) NBIS - y-axis: ZeroFAR



(h) NEURO - y-axis: ZeroFAR

Fig. 3: NBIS and NEURO performance figures of the experiments (x-axis: datasets).

genuine matching scores can be detected also with removed ghost FPs in our time-separated data. This leads to the disprove of the assumption that the observed effects are caused by ghost FP and corresponding stable minutiae information. This leads to the final statement that something different must cause the observed effects. So far it is not even clear, if decreased recognition accuracy as observed on the time separated data considered is caused by time-related or not time-related changes (i.e. differentiating between template ageing or a simple template change effect).

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