Revija za kriminalistiko in kriminologijo / Ljubljana 67 / 2016 / 4, 371–388

The Impact of Template Aging on the Performance of Automatic Fingerprint Recognition

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It is generally accepted that fingerprints do not change with age. The longstanding practice of using fingerprints for person recognition confirms this thesis, since it has been used successfully for over a century. However, in the past, person recognition based on fingerprints has been conducted only by forensic experts, but today, especially with the introduction of biometric documents, automatic person-recognition systems are in common use. But do fingerprints have enough long-term stability for reliable automatic person recognition, even with a time interval between the template- and the input fingerprint-recordings over a span of more than a decade? This paper explores the phenomenon of fingerprint template aging, i.e. an increase in the error rate of minutiae based automatic fingerprint identification systems (AFISs) recognition with increased time since fingerprint enrolment. Based on the results of statistical analysis of AFISs similarity matching scores of fingerprints pairs of all fingers of the right and left hand recorded over a span of 21 years, despite the fact that on average approx. 9% of the variability of the AFISs matching scores can be explained by template aging, we find that fingerprint template aging has a statistically significant negative impact on the performance of the AFISs, even on a relative young white-male population aged from 14 to 53 years.

Keywords: template aging, fingerprint recognition, automatic fingerprint-identification system, fingerprint persistence

UDC: 343.98

1 Introduction

All methods of person recognition, operating on the basis of humans' biometric characteristics, are based on two major assumptions: the complete uniqueness and the persistence of the measured biometric features (Pankanti, Prabhakar, & Jain, 2002). These two underlying premises are also the basis for all person-recognition methods using fingerprints. The first basic assumption is that every fingerprint is unique and it is grounded on the belief that during ridge formation, the impacts on the fingerprint's ridge patterns are mostly random. The second assumption is that the basic pattern of the fingerprint is not affected by a person's aging, i.e. that each person retains the same fingerprint pattern for the entirety of their life span. The longstanding practice of using fingerprints for person recognition (verification or identification) in police forensics confirms this thesis, since both methods have been used successfully for over a century.

The Automatic Fingerprint Identification Systems (AFISs) are also based on two basic premises: the uniqueness and the high degree of consistency of the fingerprints. However, because AFISs differ from one another in their principles of operation, they may take different approaches to matching and identifying the fingerprint patterns. Any such approach has its advantages and disadvantages, so the choice of the AFIS operation's principles is based on the requirements of the situation. Due to the robustness and insensitivity to rotation, translation and deformation of fingerprint patterns, most of the AFISs are minutiae based (Maltoni, Maio, Jain, & Prabhakar, 2009). Although this approach to fingerprint identification has proved very successful, due to the relatively short periods of widespread use of these systems, i.e., about a decade, there are no well-known influences of the elapsed time between the collected fingerprint samples. It has been observed that longer time intervals between enrolment and recognition phases lead to lower AFIS similarity matching scores due to the phenomenon known as *template aging* (Mansfield & Wayman, 2002). However, with the introduction of biometric passports and other identification documents that have recorded owners' fingerprints, usually of the index finger of the right and left hand, it has become important to discover the correlations between the AFIS recognition performance and the time elapsed between person enrolment and person recognition, especially in terms of massive automatic fingerprint verification at state borders (Hasse & Wolf, 2005).

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There is still a general belief that fingerprints do not change much with aging. Maybe this belief is the reason why there is very little literature on the template aging of fingerprints (Bowyer, 2011). Even a group of experts, gathered under the auspices of the Federal Bureau of Investigation (FBI), has concluded, based on the collected empirical research and insights into biology that the characteristics of fingerprint patterns at level I (ridges, valleys) and level II (minutiae) do not change significantly over a person's lifetime. Their opinion was that further research was needed only to verify the persistent characteristics of the fingerprint patterns at level III (pores) (Budowle, Buscaglia, & Schwartz Perlman, 2006). The second reason for the lack of literature on fingerprint template aging is the nature of fingerprint technology itself. Fingerprint sensors are a relatively new technology, and for persuasive measurements of template aging there is not a sufficient number of older fingerprint samples, so most existing studies deal with template aging over periods of a few years.

The first study on fingerprint template aging (Schuckers & Lopez, 2005) was conducted on 6000 individuals (index finger of the right and left hands) collected in a NIST database, over a three-year period. The results were mixed, because the regression line of the matching scores of the left index finger did not show any changes in this time interval, but the regression line of the matching similarity scores of the right index finger slightly declined. The study (Arnold, Busch, & Ihmor, 2005), conducted on a long-term German federal police office fingerprint database, also showed degradation in fingerprint–matching performance. An increase by a factor of 2 in terms of the FRR for time intervals of 10 years was reported. Recent study (Yoon & Jain, 2015) of longitudinal fingerprint records also confirmed that "genuine match scores tend to significantly decrease when time interval between two fingerprints in comparison increases".

This paper summarizes the study of the impacts of fingerprint template aging on the performance of minutiae based AFISs. To confirm or reject the hypothesis of fingerprint template aging, the paper introduces procedures for computing the matching scores of fingerprints from the same person, but obtained at different time intervals (up to 21 years). The study involved 1500 fingerprints from the police records of 50 people (all fingers of the right and left hand) who were recorded at three different time instances T_A, T_B, and T_C, where $T_A < T_B < T_C$. The fingerprints were obtained using the traditional ink-rolled method and then scanned into digital form. The matching scores between fingerprints from the same person obtained at three different time instances were computed with two minutiae-based AFISs: the Neurotechnology VeriFinger 6.3 AFIS (Neurotechnology, 2013), in the sequel AFIS A, and the open-source program SourceAFIS (SourceAFIS, 2013), in the sequel AFIS B, and then statistically analyzed by the use of the simple Linear Regression and one-way Analysis of Variance.

The remainder of the paper is structured as follows: In Section 2, a discussion of fingerprint persistence is presented. Section 3 describes the process of collecting fingerprints, while Section 4 describes the setup of the conducted experiments. Section 5 reports on the results of the experiments, and Section 6 includes a discussion about them. Concluding remarks are given in Section 7.

2 Persistence of Fingerprints

Although it is clear that people go through a number of changes due to the process of aging, Galton (1892) and Hershel (1916) both came to the same conclusion that the patterns of fingerprints are maintained throughout a human's life cycle, even after death, until the decomposition of the tissue begins. The first explorations of both pioneers in the field of person recognition based on fingerprints have indicated a high degree of fingerprint patterns' permanence. The thesis on the conservation of the fingerprint pattern throughout the life cycle is also confirmed by a century of successfully using fingerprints for person recognition.

2.1 Fingerprints Life-Cycle

A fetus begins to develop fingerprint patterns approximately in the sixth week of gestation, when friction ridges start to grow (Wertheim, 2011). In general, the basic characteristics of the fingerprint patterns are often genetically determined, but the details are mostly dependent on the mechanical, biological, chemical, and other influences in the uterus, which are random in nature. Therefore, relatives may have many similar basic features (Slatis, Katznelson, & Bonne-Tamir, 1976), but even identical twins with the same DNA (Deoxyribonucleic Acid) have different fingerprints (Patwari & Lee, 2008).

In childhood, the size of the fingerprint varies in proportion to the growth of the fingers, and thus the proportions of the fingerprint samples. Even after the growth period is completed, some people can experience changes in the size of a fingerprint due to a significant change in their weight. Interestingly, the majority of minor finger injuries (cuts, bruises, burns, etc.) do not alter the pattern of fingerprints, as skin restores itself almost into its original form. In exceptional cases, various factors (serious injury, diseases, inadequate environmental condition, professional malfunction, e.g., manual workers, musicians) can cause permanent changes to the skin, which consequently affect fingerprints' uniqueness (Drahansky, Brezinova, & Hejtmankova, 2010).

The quality of a fingerprint is also influenced by a person's aging, which reduces the amount of oil produced, so the skin becomes increasingly drier. Due to this loss of moisture, the skin is more rigid and inelastic, thus causing cracks and scars, which then begin to emerge in the patterns of the fingerprints. Moreover, during the aging process, the skin starts to lose the required level of collagen, which then causes softening of the fingerprint ridges. Soft, elderly fingerprint ridges can collapse into each other when the finger touches a surface during fingerprint scanning (Maceo, 2011).

However, previous studies (Modi & Elliott, 2006; Modi, Elliott, & Whetsone, 2007; Sickler & Elliott, 2005; Theofanos, Stanton, Micheals, & Orandi, 2007) have shown that in the majority of the population, these problems start to increase substantially after 60 years of age, while younger people, on average, do not have a significant deterioration in the quality of their fingerprints. Based on these studies, we can assume that the aging process in the majority of adults younger than 60 years has no significant impact on the quality of their fingerprint patterns. For the majority of people older than 60, the quality of their fingerprints begins to decline drastically. Thus, for example, the Biometrics Assurance Group (BAG) in its report (Biometrics Assurance Group, 2007) estimated that the introduction of NIS[3] in the United Kingdom (UK) is questionable, since in the UK around 4 million people are over 75 years old and it is very difficult to obtain high-quality fingerprints from them.

Figure 1 shows two right index fingerprints of the same person. The fingerprint on the left was obtained from the person at the age of 39 years using the ink-rolled method and then stored (rolled) in a personal document. The other fingerprint was obtained with the ink-rolled method from the same person at the age of 95 years.

Figure 1: Right index fingerprints obtained from a person at the age of 39 and 95 years

[3] NIS – National Identity Scheme in UK. As part of the NIS, the UK government intends to enter the personal details, including fingerprints, of every person in the UK, into a National Identity Register (Biometrics Assurance Group, 2007).

Despite the fact that at first glance the quality of both fingerprint images looks adequate, AFIS A did not give a positive match. In this particular case, we can see the effects of template aging, caused by time-related changes in the biometric pattern because of the person's aging and the effects of image degradation, caused by the aging of the paper and ink in a personal document. Note that modern personal documents (e.g., biometric passports) store biometric templates in digital form, so we do not expect any image degradation of the fingerprint templates like we saw in this particular case.

2.2 Influence of the Aging Process on Automatic Fingerprint Identification

When analysed at different scales, each fingerprint pattern exhibits different types of features. At the coarse level (Level I), the flow of the ridges and valleys generates different fingerprint patterns with singular points (arches, loops, deltas etc.). Singular points and coarse line shapes are characteristics that are mostly used for fingerprint classification and indexing, because their distinctiveness is not sufficient for an adequate differentiation in the matching processes. In addition to coarse features, a fingerprint at the local level (Level II) also contains small features called minutiae. An average fingerprint has about 30 to 40 minutiae, and each minutia is denoted by the type (termination, bifurcation), position (coordinates), and orientation (angle between the tangent to the ridge line and the horizontal axis). Minutiae–based algorithms normally also take into account some tolerances, mainly due to abnormalities that arise during the fingerprinting. Such distortions are mostly random, since they mainly depend on the amount of pressure from the finger on the surface and its position (Maltoni et al., 2009).

All previous studies have confirmed that a person's aging process leads to a decrease in fingerprint quality and thus also has an effect on the AFISs performance. However, the AFISs matching scores of the fingerprint comparisons obtained at different time periods show that in terms of AFISs performance, besides the age of the person, there is a large influence from the time interval between the fingerprint recordings. It turned out that on average (where other effects were more or less eliminated) the AFIS matching scores of the fingerprint comparisons of fingerprints collected from older people over a short period of the time are higher than the AFISs matching scores for the comparisons of the same people with the fingerprints taken in their youth. It is assumed that the fingerprints obtained in their youth, on average, are of a higher quality than the fingerprints when they are older. Given that the fingerprints were recorded from people aged from 14 to 53 years, where the quality of the fingerprints are relatively stable due to the relatively young age of those printed, such results can be explained only by the strong influence of a temporal component among the fingerprints for AFIS. This means that the fingerprints are not completely persistent and that a person's aging process also has an influence on the fingerprint features, which the AFISs use in the person-recognition processes.

Figure 2 shows the fingerprints of a person's left middle finger obtained at the age 27, 36, 37, 38, 38.5, and 39 years, from the police records.

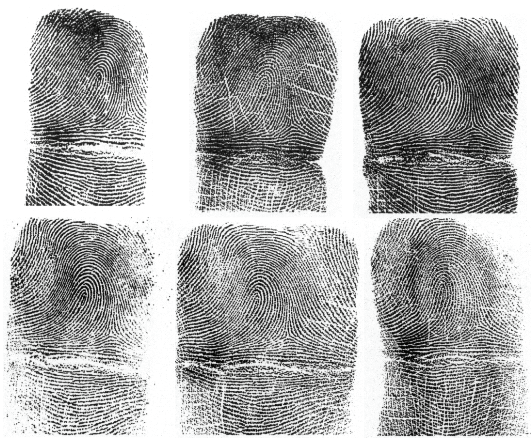


Figure 2: Rolled fingerprints obtained from a person at the age of 27, 36, 37, 38, 38.5 and 39 years

At first glance we can see that the quality of the prints does not differ very much. However, it is interesting to note the cracks on the fingerprint at 36 years; these almost disappear on the older fingerprints and new ones appear. This suggests that the quality of the fingerprints also depends on the current moisture level of the skin, regardless of the person's age. Many similar cases were also identified in other fingerprints; in particular, we found that younger people have, on average, moister fingers and thus darker fingerprints.

Table 1 shows the Matching-Similarity-Scores Matrix (Carls, Raines, Grimaila, & Rogers, 2008) calculated from the AFIS A matching scores for peer comparisons of fingerprints in Figure 2.

Table 1: Similarity-matching-scores matrix for the left middle finger

Age (years)	27	36	37	38	38.5	39
27	**1946**	**378**	**407**	**360**	**203**	**327**
36	**378**	**2118**	**371**	**197**	**176**	**267**
37	**407**	**371**	**2310**	**447**	**456**	**365**
38	**360**	**197**	**447**	**2256**	**759**	**404**
38.5	**203**	**176**	**456**	**759**	**2111**	**317**
39	**327**	**267**	**365**	**404**	**317**	**2352**

Although the AFISs matching scores also depend on the quality of each particular fingerprint, in Table 1 a downward trend in the matching scores, depending on the time frame between the matched fingerprints (the row elements from the diagonal), can be observed, which supports the theory of decreasing fingerprint quality due to a person's aging. In Table 1 we can also observe that the matching scores of fingerprints obtained in shorter periods of time (6 months, one, two or three years), despite the increased age of the person, on average, are better than the matching scores of fingerprints taken over longer periods of the time (nine to twelve years). These results allow us to speculate that the AFIS matching scores change not only because of the reduced quality of the fingerprints caused by a person's aging processes, but also because of the template aging, which indicates that the fingerprint patterns are not completely persistent.

Of course, the aforementioned example does not constitute conclusive evidence that would refute the theory of the temporal persistence of fingerprints, but it indicates the problems that the minutiae-based AFISs face when comparing fingerprints obtained over longer time periods.

2.3 Template Aging – Discovering the Non-Persistence of Fingerprints

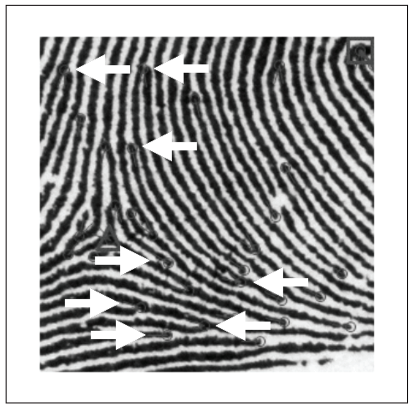
Galton (1892) observed that with some rare fingerprints, which were obtained after a long time interval, there were clear, unexplained changes to the small features at level II (minutiae). In our research, we also detected some strange changes to minutiae over long time intervals.

Figure 3 shows two fingerprints in our database obtained from a person at ages 18 and 38 years, where an obvious bifurcation after twenty years simply disappeared. One logical reason for this change could be an injury, which could cause the displacement of ridges in the healing process of the wounds. In favour of this assumption are the disconnected and indented ridges that form a virtual line passing through the area where it clearly should be a bifurcation.

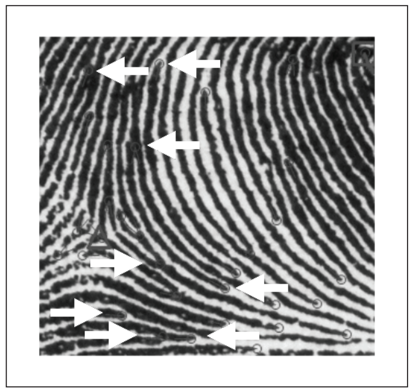
Figure 3: Fingerprints obtained from a person at 18 and 38 years

As such obvious changes are very rare; we presume that, on average, they cannot have a significant negative impact on the AFISs performance. To uncover more significant impacts on AFISs as a result of a person's aging, we analysed fingerprint images after AFIS post-processing, where we noticed that subsequent processing of fingerprint images in the AFIS often led to confusion between bifurcations and ridge endings. This effect is very common because of the random deformation of fingerprint patterns caused by likewise random pressure during the fingerprint's capture. Random deformations result in minimal changes in the direction of ridge endings, which leads to misinterpretations of minutiae types. This effect is more obvious for fingerprints obtained over different time periods, as the person's aging processes cause minimal changes to the bifurcations and ridge endings. In some cases the slope of the ridge changes even leads to the ridge's fusion or splitting.

Figure 4 shows parts of the fingerprints taken from a person at the ages of 19 and 39 years, where we can see different AFIS A interpretations of the minutia type. We can see 32 minutiae on selected areas of both fingerprints, but AFIS A defines 8 of them differently on each fingerprint. Some minutia type changes can be clearly observed, even visually, as true, small, physical fingerprint changes. Other minutiae type errors are caused by the decisions of the AFIS A.



a)



b)

Figure 4: Fingerprints obtained from a person at the ages: a) 19 years and b) 39 years

Because the scores of minutiae-based fingerprint matching algorithms are strongly correlated with the correct identification of minutia types, it is quite clear that, by increasing the number of false minutiae types, the fingerprints similarity matching scores decrease.

3 Data Set

Since most modern AFISs obtain digital fingerprint images from fingerprint readers, for a more credible analysis of the impact of a person's aging on the operation of AFISs, we should use fingerprint samples obtained by fingerprint readers. However, it is practically impossible to obtain a sufficient quantity of such fingerprints older than ten years, as the fingerprint readers prior to this period were more experimental in the nature. Therefore, the only opportunity for research on the impact of template aging on the performance of AFISs is to study police records of fingerprints that were obtained by the traditional "ink-and-roller method", and then scanned into a digital form.

The question then arises as to whether it is possible to generalize the study results to other digital fingerprint acquisition methods. In an extensive study that included a large number of fingerprints in the FBI records obtained in the traditional way by using ink and paper, as well as with fingerprint readers, no major difference was found between the operations of the AFIS, regardless of the method of sampling (Wilson, Watson, Garris, & Hicklin 2003).

In addition to the suitability of scanned fingerprints from the police records, which were obtained using ink, there is also the problem of obtaining adequate fingerprint samples. For research on the persistence of fingerprints, there is the requirement of fingerprint samples that were taken over a long period of time, which means the police files of older people, who are rarely arrested. Because these older people must have also had police records from their youth, the selection of suitable candidates was further reduced.

In our research, we had the fingerprints of 50 people (white males) which were obtained during their arrest. In all such cases, the police recorded the fingerprints of all fingers of the right and left hand. All the survey participants had at least three records, one from the year 2010 (T_C), the second mostly from the year 2008 or 2009 (T_B), and the third older than the previous two, usually from the person's youth (T_A). Each police record was scanned with a flatbed scanner and all the fingerprints were cut and pasted to pictures. Because of AFISs software demands and quality requirements, all the fingerprints were stored in the JPG picture format with a size of 750x900 pixels.

Mathematically, we can represent our data set as a set $\mathcal{FP}$ consisting of 1500 scanned fingerprint images of all fingers of the right and left hand collected from 50 survey participants in 3 sessions:

$$\mathcal{FP} = \{FP_1, FP_2,..., FP_{1500}\}, \tag{1}$$

where each fingerprint image $FP_i \in \mathcal{FP}$ has the following additional (meta-) data: (i) survey participant ID (*FP*.id = ID code), (ii) date of the birth (*FP*.dateB = Date of birth), (iii) date of the fingerprint registration (*FP*.dateC = Date of fingerprint registration), and (iv) the fingerprint description (right or left hand and name of the finger) (*FP*.fingerID = RT – Right Thumb, LT – Left Thumb, RI – Right Index, LI – Left Index, RM – Right Middle, LM – Left Middle, RR – Right Ring, LR – Left Ring, RP – Right Pinky, LP – Left Pinky).

For each survey participant *S*, we define a subset of fingerprint images $FP \in \mathcal{FP}$ as follows:

$$\mathcal{FP}_S = \{FP \in \mathcal{FP} \mid FP.id = S\},\ s = 1, 2, ..., 50. \tag{2}$$

Each set $\mathcal{FP}_S$ is an union of subsets $\mathcal{FP}_S^{\,A}$, $\mathcal{FP}_S^{\,B}$, and $\mathcal{FP}_S^{\,C}$ containing fingerprint images of the survey participant's 10 fingers collected at the time instances T_A, T_B, and T_C, where $T_A < T_B < T_C$, respectively:

$$\begin{aligned}\mathcal{FP}_S^{\,A} &= \{FP_A \in \mathcal{FP}_S \mid FP.dateC = T_A\},\\ \mathcal{FP}_S^{\,B} &= \{FP_B \in \mathcal{FP}_S \mid FP.dateC = T_B\},\\ \mathcal{FP}_S^{\,C} &= \{FP_C \in \mathcal{FP}_S \mid FP.dateC = T_C\},\end{aligned} \tag{3}$$

Figure 5 shows side-by-side boxplots of survey participants' ages at the first fingerprint recordings (T_A), at the second fingerprint recordings (T_B), and at the last fingerprint recordings (T_C).

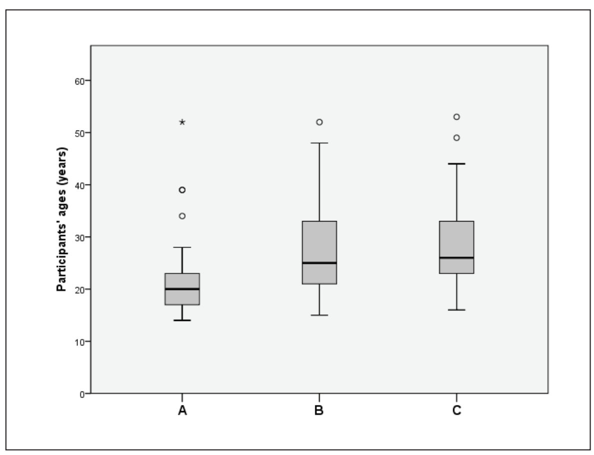


Figure 5: Side-by-side boxplots of survey participants' ages at the first (A), at the second (B) and at the last (C) fingerprint recording

3.1 Quality of the Digital Fingerprint Images

The quality of the digital fingerprint image can be defined in different ways and there is no complete agreement on this issue in the literature (Tabassi, Wilson, & Watson, 2004). Common to all approaches to measuring the quality of fingerprint images is the expectation that a better quality of the fingerprint images gives better AFISs matching scores. NIST even defines digital fingerprint image quality as a "predictor of a matcher's performance" (Tabassi et al., 2004).

Regardless of the approach to its measuring, the quality of fingerprint images is affected by several factors. In general, impacts on fingerprint quality can be divided into influences that are dependent on the scanning processes, and the influences of the physiological and physical characteristics of the concerned persons. The scanning process's influences can also be divided into equipment impacts (ink, type of scanning sensors), influences that are dependent on the involved personnel (professionalism), and the treated persons (collaboration in the process, deformity due to pressure). The physiological and physical characteristics of those treated can depend on many factors that may be subjective in nature, since they depend largely on the person's characteristics (gender, genetics, race, age, welfare, illness, occupation, etc.); and factors of an objective nature, mainly dependent on environmental characteristics (temperature, season, anxiety at the time of the arrest and stress that could cause skin moisture, etc.).

For measuring the quality of the digital fingerprint images, we used MITRE´s program IQF (Image Quality of Fingerprint), which computes a digital fingerprint image's visual quality based on the two-dimensional, spatial frequency, power spectrum of the image (Nill, 2007). By choosing this approach to measuring the quality of the digital fingerprint images, we wanted to make sure that the AFIS results are not too dependent on the physical characteristics of the concerned persons.

Figure 6 displays the image quality of 1500 scanned fingerprint images of all fingers of the right and left hand collected from 50 survey participants over 3 sessions. The IQF test result for each digital fingerprint image is an integer number, representing the sum of the filtered, scale-weighted values of the power spectrum. The values can range from 0, indicating the worst possible quality, up to the value of 100, which represents the best quality of a fingerprint image.

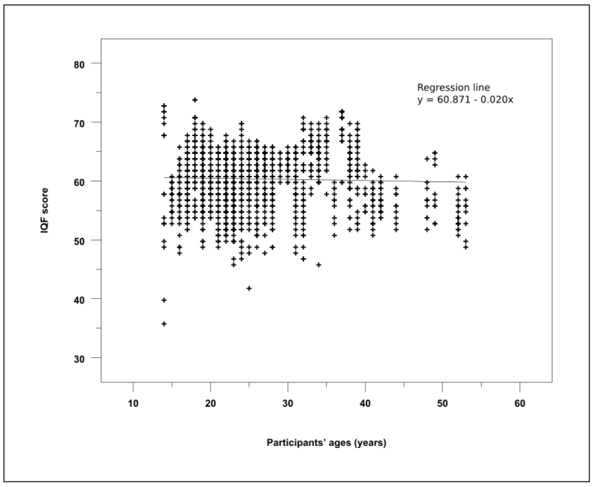


Figure 6: Scattergram and regression line of the image quality of 1500 fingerprint images measured by MITRE's IQF program as a function of the survey participants' ages

The fingerprint image quality measured by the MITRE´s IQF program is seen to be almost evenly distributed for people age 14 to 40 years and for this time period we can calculate an almost flat regression line. For people over 40 years, most of the fingerprint samples did not exceed the linear regression line. The interesting part is that many young people also had very poor results for fingerprint image quality. The reason for this may be due to the stress endured by the young people during their arrests, as most of the fingerprint samples with fingerprint images in this age group had more darkness, as a result of increased moisture.

4 Experimental Set-Up

To explore the impact of template aging on the performance of AFISs, the AFISs' matching scores were computed by comparing fingerprints from the same person recorded in the time instances T_A, T_B and T_C. For this purpose two minutiae-based AFISs were chosen: a commercial state-of-the-art AFIS A and an open-source AFIS B.

For each survey participant S and each AFIS, a set of similarity matching scores $\mathcal{M}_S$ is generated:

$$\mathcal{M}_S = \{M_{ij}\,(FP_i,\, FP_j) \mid FP_i \in \mathcal{FP}_S^{\,i},\, FP_j \in \mathcal{FP}_S^{\,j}\}, \qquad (4)$$

where M_{ij} denotes AFIS's similarity matching score between fingerprint recordings from a survey participant obtained in time instances i and j; $i \in \{A, B\}$, $j \in \{B, C\}$, $i \neq j$.

Defining time intervals between fingerprint recordings from a survey participant obtained in time instances T_A, T_B, and T_C as:

$$\begin{aligned} &\Delta T_{AC} = T_C - T_A, \\ &\Delta T_{AB} = T_B - T_A, \text{ and} \\ &\Delta T_{BC} = T_C - T_B, \end{aligned} \tag{5}$$

each set $\mathcal{M}_S$ can be represented as a union of subsets $\mathcal{M}_S^{AC}$, $\mathcal{M}_S^{AB}$, and $\mathcal{M}_S^{BC}$, which contains fingerprints matching scores of 10 survey participant's fingers for time intervals between recordings ΔT_{AC}, ΔT_{AB}, and ΔT_{BC}, respectively, where:

$$\begin{aligned} &\mathcal{M}_S^{AC} = \{M_{AC}(FP_A, FP_C) \mid FP_A \in \mathcal{FP}_S^A, FP_C \in \mathcal{FP}_S^C\} \\ &\mathcal{M}_S^{AB} = \{M_{AB}(FP_A, FP_B) \mid FP_A \in \mathcal{FP}_S^A, FP_B \in \mathcal{FP}_S^B\} \\ &\mathcal{M}_S^{BC} = \{M_{BC}(FP_B, FP_C) \mid FP_B \in \mathcal{FP}_S^B, FP_C \in \mathcal{FP}_S^C\} \end{aligned} \tag{6}$$

By $\mathcal{M}^{AC}$, $\mathcal{M}^{AB}$, and $\mathcal{M}^{BC}$ we denote a union of 50 subsets of the matching scores $\mathcal{M}_S^{AC}$, $\mathcal{M}_S^{AB}$, and $\mathcal{M}_S^{BC}$, respectively. Fig. 7 shows side-by-side boxplots of the time intervals between fingerprint recordings ΔT_{AC}, ΔT_{AB}, and ΔT_{BC} in the sets $\mathcal{M}^{AC}$, $\mathcal{M}^{AB}$, and $\mathcal{M}^{BC}$, respectively.

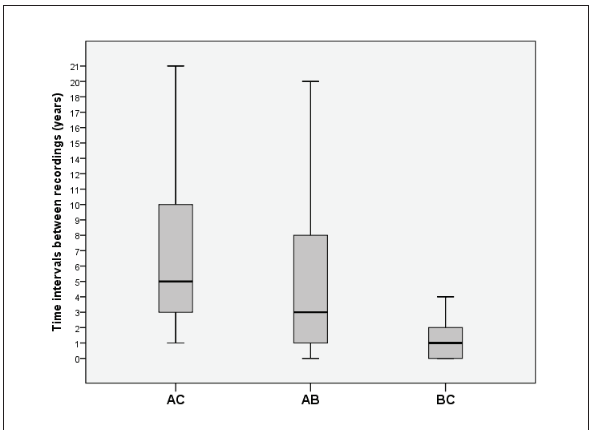


Figure 7: Side-by-side boxplots of the time intervals between the first and last fingerprint recordings (ΔT_{AC}), the first and second fingerprint recordings (ΔT_{AB}), and the second and last fingerprint recordings (ΔT_{BC}) in the sets $\mathcal{M}^{AC}$, $\mathcal{M}^{AB}$, and $\mathcal{M}^{BC}$

4.1 Testing the Hypothesis of Fingerprint Template Aging

In order to confirm or reject the hypothesis of fingerprint template aging, we conducted two experiments. In the first, we compared the sets of AFISs matching scores $\mathcal{M}_f^{AC}$, $\mathcal{M}_f^{AB}$, $\mathcal{M}_f^{BC}$ and for each finger f of the right and left hand separately, to test whether the sets $\mathcal{M}_f^{AC}$, $\mathcal{M}_f^{AB}$, and $\mathcal{M}_f^{BC}$ were samples drawn from three different populations. For this purpose, we formulated the null hypothesis that there is no statistically significant difference among mean values μ_f^{AC}, μ_f^{AB} and μ_f^{BC} of the sets of fingerprints matching scores, $\mathcal{M}_f^{AC}$, $\mathcal{M}_f^{AB}$, and $\mathcal{M}_f^{BC}$, respectively, i.e.:

$$H_0 : \mu_f^{AC} = \mu_f^{AB} = \mu_f^{BC}, \tag{7}$$

where f is abbreviation of the hand and finger name; $f \in \{RT, RI, RM, RR, RP, LT, LI, LM, LR, LP\}$, and checked H_0 using the one-way Analysis of Variance (one-way repeated measures ANOVA) technique.

In the second experiment, we used a simple Linear Regression technique to analyse the AFISs matching scores from the set of matching scores of the longest time intervals between fingerprint recordings $\mathcal{M}_f^{AC}$; where $f \in \{RT, RI, RM, RR, RP, LT, LI, LM, LR, LP\}$, as a function of the "length of time intervals between the fingerprint recordings". In order to evaluate the significance of the linear relationship between the independent variable – "length of time intervals between fingerprint recordings" and the dependent variable – "AFIS similarity matching scores", we used the ANOVA F-test of hypothesis for the significance of the simple Linear Regression (Miller & Haden, 2006). For this purpose, we formulated the null hypothesis that the regression line is not significant, i.e.:

$$H_0 : \beta_1 = 0, \tag{8}$$

where β_1 represents the slope of the regression line.

4.2 Assumptions of One-Way Repeated Measures ANOVA and Simple Linear Regression

As with most statistical procedures, one-way repeated measures ANOVA and simple Linear Regression make certain assumptions about the data used in analysis. In the case that these assumptions are violated, the results of the analysis may not be valid (Boslaugh & Watters, 2008; Milliken & Johnson, 1993). Key assumptions for:

i. one-way repeated measures ANOVA are: (a) the dependent variable is continuous, independent variable categorical; (b) approximately normally distributed; (c) the variances of the differences between all combinations of related groups must be equal (sphericity). The first assumption is fulfilled in the proper design of the experiment, but the last two have to be tested.

ii. simple Linear Regression are: (A) dependent variables is continuous and stochastic in nature, (B) each value of dependent variable is independent of each other, (C) relationship between the variables is linear in nature, (D) the variance of errors of prediction (residuals) is constant over the entire data range (homoscedasticity), (E) the error of prediction for each data point is independent of the error of prediction for each other data point, and (F) the errors of prediction should be normally distributed. The first two assumptions are fulfilled in the proper design of the experiment, but the last four have to be tested.

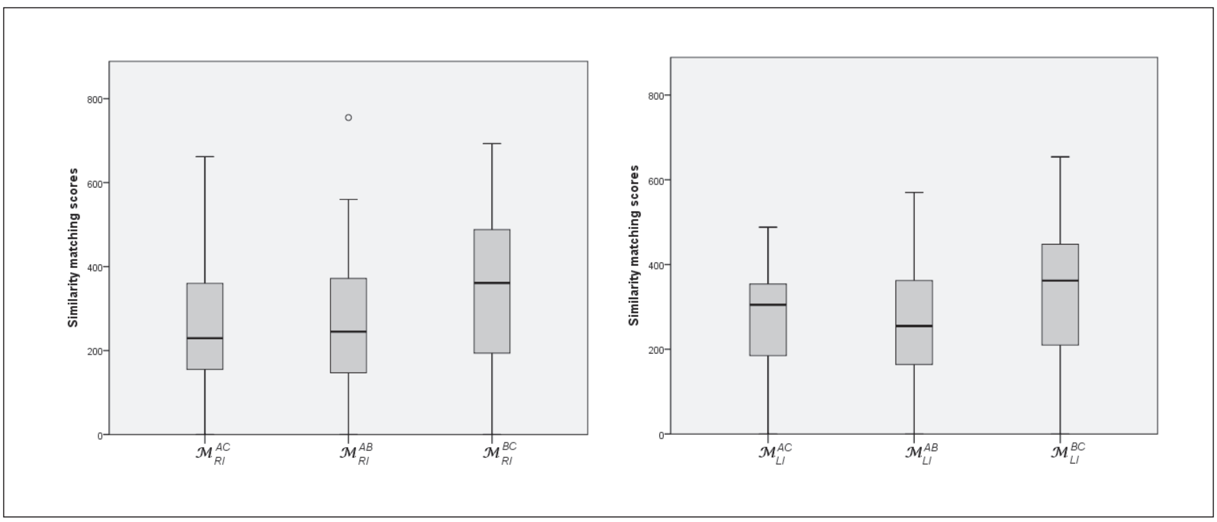
We will start both statistical procedures by testing the above-mentioned assumptions: the normality of data distribution by the use of the Kolmogorov-Smirnov test (Panchenko, 2006), sphericity by the use of the Mauchly's test (Mauchly, 1940), linear relationship between variables by the use of the Linearity test (Miller & Haden, 2006) and the Deviation from linearity test (Miller & Haden, 2006), the homoscedasticity by the use of the Breusch-Pagan test for heteroscedasticity (Breusch & Pagan, 1979), and the independence of data by the use of the Durbin-Watson test (Durbin & Watson, 1950). We will refer to p-value < 0.05 as the criterion for deciding to reject the null hypothesis. All statistical analyses were performed by the use of IBM® SPSS Statistics V.19.0 (IBM, 2013).

5 Results

As the results of statistical analyses of the sets of matching scores of fingerprints from all ten fingers with two AFISs are presented with a great number of tables and graphs, in this section we describe in detail only statistical analyses of sets of matching scores of fingerprints of index finger of the right and left hand (fingers, whose fingerprints are commonly saved on biometrics documents) obtained with AFIS A. We conclude by presenting the graphs of regression lines for fingerprints of all ten fingers and for both AFISs.

5.1 Experiment I

In this experiment, we have tested the null hypothesis (eq. 7) by use of the one-way repeated measures ANOVA test of hypothesis, and as the null hypothesis was rejected, we ran Tukey's honestly significant difference (HSD) post hoc test (Milliken & Johnson, 1993) to see which set mean differ from the rest. The analysed sets of AFIS A matching scores $\mathcal{M}_{RI}^{AC}$, $\mathcal{M}_{RI}^{AB}$, and $\mathcal{M}_{RI}^{BC}$, as well as sets $\mathcal{M}_{LI}^{AC}$, $\mathcal{M}_{LI}^{AB}$ and $\mathcal{M}_{LI}^{BC}$, are displayed by their boxplots in Figure 8.



a) b)

Figure 8: Side-by-side boxplots of: a) $\mathcal{M}_{RI}^{AC}$, $\mathcal{M}_{RI}^{AB}$, and $\mathcal{M}_{RI}^{BC}$; b) $\mathcal{M}_{LI}^{AC}$, $\mathcal{M}_{LI}^{AB}$ and $\mathcal{M}_{LI}^{BC}$

From the description of the data set collection process (see Section 3) and experimental set–ups (see Section 4) follow that in the test the independent (group) variable – "time intervals between fingerprint recordings ΔT_{AC}, ΔT_{AB}, and ΔT_{BC}" – is categorical, and the dependent (outcome) variable – "AFIS A matching scores" – is continuous, as well as that the values of the dependent variable within the sets are independent. Prior to testing null hypothesis (eq. 7), we tested the one-way repeated measures ANOVA assumptions (b) and (c).

To verify if the AFIS A matching scores in each set of scores $\mathcal{M}^{AC}_{RI}$, $\mathcal{M}^{AB}_{RI}$, $\mathcal{M}^{BC}_{RI}$, $\mathcal{M}^{AC}_{LI}$, $\mathcal{M}^{AB}_{LI}$, and $\mathcal{M}^{BC}_{LI}$ follows the normal distribution, we formulated the null hypothesis that AFIS A matching scores follows the normal distribution and computed the Kolmogorov-Smirnov statistics. As all p-values are greater than the significance level 0.05, the null hypothesis that the data follow the normal distribution is not rejected for all sets of AFIS A matching scores. The results are summarized in Table 2.

Table 2: Results of Kolmogorov–Smirnov tests

	$\mathcal{M}^{AC}_{f}$		$\mathcal{M}^{AB}_{f}$		$\mathcal{M}^{BC}_{f}$	
f	***K-S statistic***	***p-value***	***K-S statistic***	***p-value***	***K-S statistic***	***p-value***
RI	0.1219	0.0610	0.1184	0.0773	0.0992	0.2000*
LI	0.1097	0.1841	0.1174	0.0826	0.1243	0.0518

* This is a lower bound of the true significance.

The assumption (c) that the variances of the differences between all combinations of related groups (the sets $\mathcal{M}^{AC}_{RI}$, $\mathcal{M}^{AB}_{RI}$, and $\mathcal{M}^{BC}_{RI}$, as well as the sets $\mathcal{M}^{AC}_{LI}$, $\mathcal{M}^{AB}_{LI}$, and $\mathcal{M}^{BC}_{LI}$) must be equal, was tested by the use of Mauchly 's test. As Mauchly's test of LI finger indicated that the assumption of sphericity has been violated ($\chi^2(2)$ = 6,1252, p-value = 0.0468), degrees of freedom were corrected using the Huynh-Feldt procedure (Huynh & Feldt, 1976).

As all ANOVA's assumptions are met, the null hypothesis (eq. 7) is tested by the one-way repeated measures ANOVA test of hypothesis for both triplets of sets of the AFIS A matching scores $\mathcal{M}_f^{AC}$, $\mathcal{M}_f^{AC}$, and $\mathcal{M}_f^{BC}$. The results of the Mauchly's and ANOVA tests are summarized in Table 3.

Table 3: Results of Mauchly's and ANOVA tests

	Mauchly's Test of sphericity		***ANOVA***	
f	***Mauchly's statistic***	***p-value***	***F statistic***	***p-value***
RI	0.9012	0.0824	9.9385	0.0001
LI	0.8802	0.0468	9.0735*	0.0004*

* Degrees of freedom were corrected using Huynh-Feldt procedure

As both p–values of ANOVA F-test are less than the significance level 0.05, the null hypothesis (eq. 7) is rejected for both triplets of sets. The obtained results tell us that in each triplet of data sets, the means of at least two of data sets differ significantly. To answer the question of which sets differ from each other, we conducted the Tukey's HSD post-hoc test. The results of the test are summarized in Table 4.

Table 4: Results of Tukey's HSD post-hoc tests

	(I) (J)	***Mean differences, (I-J)***	***Std. Error***	***p-value***
$\mathcal{M}^{IJ}$ ***RI***	***AB AC***	-13.340	32.174	0.9097
	BC	-94.580	32.174	0.0106
	AC AB	13.340	32.174	0.9097
	BC	-81.240	32.174	0.0336
	BC AB	94.580	32.174	0.0106
	AC	81.240	32.174	0.0336
$\mathcal{M}^{IJ}$ ***LI***	***AB AC***	5.500	29.220	0.9807
	BC	-69.160	29.220	0.0501
	AC AB	-5.500	29.220	0.9807
	BC	-74.660	29.220	0.0311
	BC AB	69.160	29.220	0.0501
	AC	74.660	29.220	0.0311

We can note that for both fingers, the mean differences in the means of sets $\mathcal{M}_f^{BC}$ and $\mathcal{M}_f^{AC}$ are significant at the level 0.05 (p-value < 0.05). Also, the mean differences in the means of sets $\mathcal{M}_{RI}^{BC}$ and $\mathcal{M}_{RI}^{AB}$ are significant at the level 0.05, but not for sets $\mathcal{M}_{LI}^{BC}$ and $\mathcal{M}_{LI}^{AB}$, where p-value is 0.0501. The mean differences in the means of sets $\mathcal{M}_f^{AC}$ and $\mathcal{M}_f^{AB}$, where $f \in \{RI, LI\}$, is not significant at all.

For the index finger of the right and left hand, the results obtained show the following:

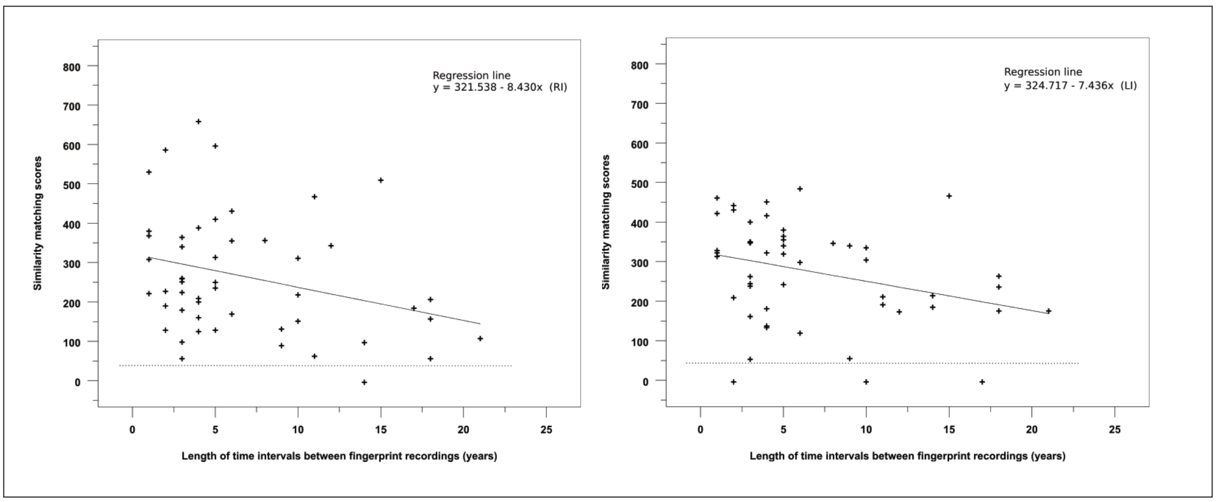
a) mean values of sets $\mathcal{M}_f^{AC}$ and $\mathcal{M}_f^{AB}$ significantly differ from the mean value of the set $\mathcal{M}_f^{BC}$;

b) sets $\mathcal{M}_f^{AC}$ and $\mathcal{M}_f^{AB}$ are drawn from the same population, which we can call "matching scores of long-time intervals (LTI) between fingerprint recordings", while the set $\mathcal{M}_f^{BC}$ is drawn from a different population, which we can call it "matching scores of short-time intervals (STI) between fingerprint recordings".

confine ourselves to present the results obtained on the set of the longest time intervals between fingerprint recordings $\mathcal{M}_f^{AC}$.

The scattergrams of the AFIS A matching scores sets $\mathcal{M}_{RI}^{AC}$ and $\mathcal{M}_{LI}^{AC}$ as a function of the length of time intervals between fingerprint recordings are displayed in Figure 9. The scattergrams confirm that both variables are continuous and have substantial ranges, as well as that we have 100 cases with values for both variables. The dependent variable (regressand) is a stochastic variable, but the independent variable (regressor) is non-stochastic and it is measured (computed) without any error. From the description of the data set collection process (see Section 3) and experimental set-ups (see Section 4), it follows that the values of the dependent variable are mutually independent.

We start the simple Linear Regression analysis by testing assumption C). To check assumption C) – linear relationship



a) b)

Figure 9: Scattergrams and regression lines of the AFIS A sets of matching scores: a) $\mathcal{M}_{RI}^{AC}$ and b) $\mathcal{M}_{LI}^{AC}$ as a function of the length of time intervals between fingerprint recordings. The dotted horizontal line on the bottom of both subfigures denotes AFIS A predefined threshold matching score, which determines identification decision. It is set at False-Acceptance-Rate (FAR) of 0.01%

5.2 Experiment II

Based on the results of the previous experiment, here we use the simple Linear Regression technique, and analyse sets of matching scores of long time intervals between fingerprint recordings $\mathcal{M}_f^{AC}$ and $\mathcal{M}_f^{AB}$ as a function of the length of time intervals between the fingerprint recordings. In the sequel, we

between the dependent and independent variable – we defined the null hypothesis that a linear model is appropriate, and conducted the Linearity and the Deviation from linearity tests. Table 5 shows results of the Linearity and the Deviation from linearity tests of the fingerprints of the right and left index finger.

Table 5: Results of Linearity and Deviation from linearity tests and Simple Linear Regression coefficients

	Linearity test		Deviation from linearity test		Linear Regression coefficients	
f	*F statistic.*	*p-value*	*F statistic*	*p-value*	β_0	β_1
RI	4.5761	0.0397	0.9501	0.5198	321.538	-8.430
LI	4.8904	0.0338	0.8120	0.6514	324.717	-7.436

A small significance value of the Linearity test (p-value < 0.05) and a relatively high significance value of the Deviation from linearity test (p-value > 0.05) suggest that the null hypothesis, namely that a linear regression model is appropriate, is not rejected. Table 5 also shows the coefficients of the linear regression lines (the intercept of the line on *Y*-axis β_0 and the line slope β_1), which minimize the sum of squared differences between observed values and predicted values of the dependent variable.

The ANOVA *F*-test of hypothesis was performed to confirm or to reject the null hypothesis (eq. 8) that the regression lines in Fig. 9 are not significant. Results are presented in the first two columns of Table 6.

Table 6: Results of ANOVA hypothesis tests, the Pearson's correlation coefficients *r*, and the coefficients of determination r^2

	ANOVA		Pearson's statistics	
f	*F statistic*	*p-value*	*r*	r^2
RI	4.6437	0.0362	-0.2970	0.0882
LI	4.1742	0.0274	-0.3119	0.0973

The results of the ANOVA test of hypothesis in the first two columns of Table 6 tell us to reject the null hypothesis (eq. 8) at the level of significance 0.05, therefore we can conclude that the length of time intervals between fingerprint recordings (Template aging) is a significant predictor of the AFIS A similarity scores of fingerprints of the index finger of the right and left hand. The results in the third column of Table 6 indicate a weak negative linear relationship between the AFIS A similarity matching scores of fingerprints of the index finger of the right and left hand and the template aging, and finally the results in the last column of Table 6 show that only approx. 8 % to 10 % of total variation of the AFIS A similarity matching scores of fingerprints of the index finger of the right and left hand can be explained by the linear relationship with the template aging.

Our final steps are to finish checking the simple Linear Regression assumptions to be sure that the regression results are valid. The assumption that the variance of errors of prediction (residuals) is constant over the entire data range (homoscedasticity) was examined on the plot of standardized residuals against the standardized predicted values as well as by the use of the Breusch-Pagan (B-P) test for heteroscedasticity. In order to confirm the assumption of homoscedasticity of standardized errors of prediction, we have defined the null hypothesis that standardized errors of prediction have constant variance and conducted the B-P test. The results are presented in Table 7, which tell us not to reject the null hypothesis (all p-values > 0.05), so we conclude that the simple Linear Regression assumption D is met for both fingers.

We tested the assumption that the error of prediction for each data point is independent of the error of prediction for each other data point (assumption E) using the Durbin-Watson (D-W) test, and finally, we checked the normality of errors of prediction (assumption F) by conducting the Kolmogorov-Smirnov test. The values of the D-W and the K-S statistics are listed in Table 7.

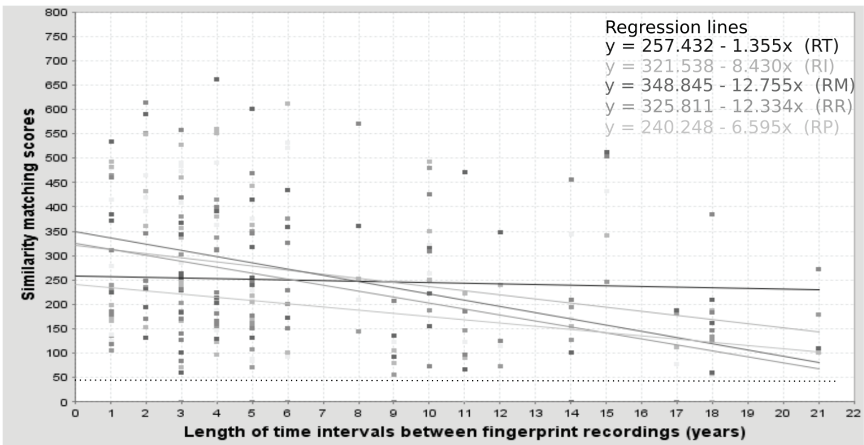
The D–W statistic ranges from 0 to 4 and the value of 2 indicate complete independence of errors of prediction. Referring to figures in Table 7, we can say that the assumption that the error of prediction for each data point is independent of the error of prediction for each other data point is met. As the p-values of the K-S test for the index finger of both hands are greater than the significance level 0.05, the null hypothesis that the errors of prediction follow the normal distribution is not rejected.

As for the fingerprints of the index finger of the right and left hand, the simple Linear Regression assumptions are satisfied, so we can conclude that the use of a linear regression model for purposes of inference or prediction of AFIS A matching scores is justified.

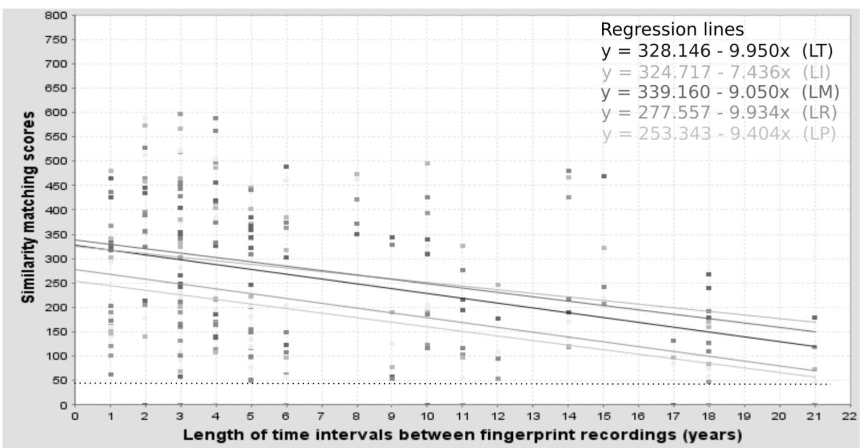
We end the section by presenting the graphs of regression lines for fingerprints of all ten fingers and for both AFISs. Figures 10 a) and 10 b) display the scattergrams and the regression lines of the AFIS A matching similarity scores for each finger of the right and left hand as a function of the length of time between the recordings of the matched samples.

Table 7: Results of Breusch-Pagan, Durbin-Watson, and Kolmogorov-Smirnov tests (Errors of Prediction)

	Breusch-Pagan tests		*Durbin-Watson tests*	*Kolmogorov-Smirnov tests*	
f	***B-P statistic***	***p-value***	***D-W statistic***	***K-S statistic***	***p-value***
RI	0.084	0.7721	1.9454	0.1092	0.1892
LI	0.061	0.8053	2.0160	0.0951	0.2000*



a)

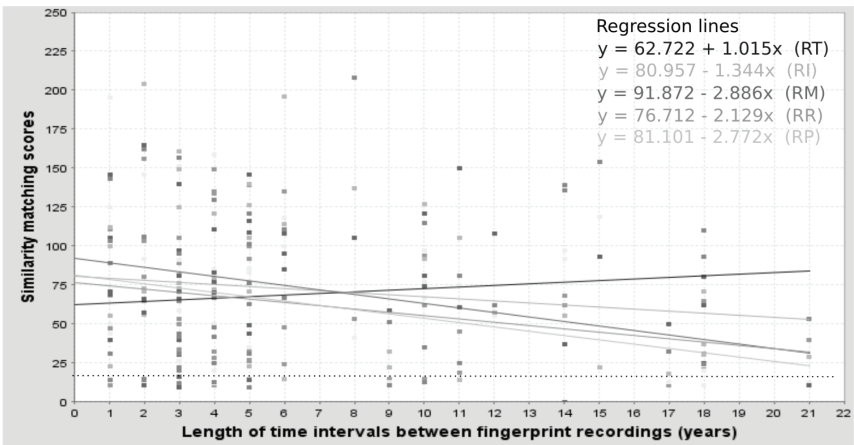


b)

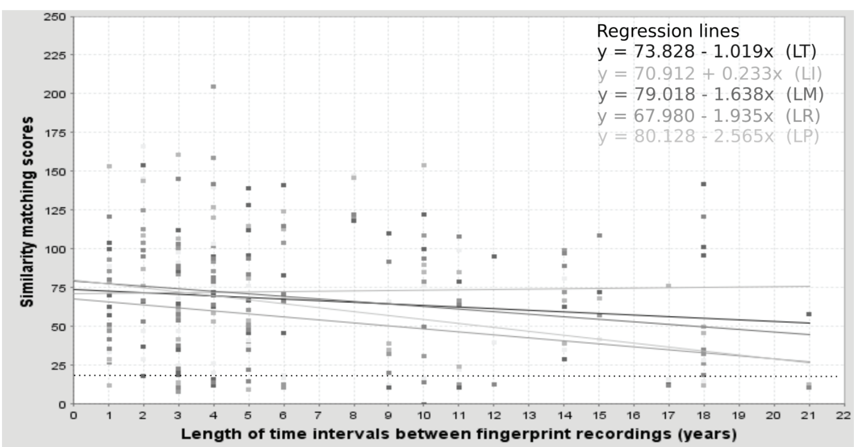
Figure 10: Scattergram and the regression lines of the AFIS A matching similarity scores for each finger of the a) right and b) left hand as a function of the length of the time interval between the recordings of the matched fingerprint samples. The dotted horizontal line on the bottom of both subfigures denotes AFIS A predefined threshold matching score, which determines identification decision. It is set at False-Acceptance-Rate (FAR) of 0.01%

In Figure 10, we see that the AFIS A matching similarity scores of the right hand show a higher diversity than the matching similarity scores of the left hand. In Figure 10 a), the regression lines of the matching similarity scores of the index and the middle fingers with increasing time interval decline differently than the regression line of the matching scores of the thumb, which has also a lower y-intercept, while in Figure 10 b), the regression lines of the AFIS A matching scores of the thumb, index, and middle fingers on the left hand are almost identical for the whole time scale, while the regression lines of the matching scores of the ring and the pinky finger are lower, especially for the pinky, which is logical, since these fingerprints are smaller and thus have a smaller number of minutiae.

Figures 11 a) and 11 b) display the scattergrams and the regression lines of the AFIS B matching similarity scores for each finger of the right and left hand as a function of the length of time between the recordings of the matched fingerprint samples.



a)



b)

Figure 11: Scattergram and the regression lines of the AFIS B matching similarity scores for each finger of the a) right and b) left hand as a function of the length of the time interval between the recordings of the matched fingerprint samples. The dotted horizontal line on the bottom of both subfigures denotes AFIS B predefined threshold matching score

The AFIS B similarity matching scores are lower than the AFIS A similarity matching scores and the regression lines are flatter. In contrast to the AFIS A, which rejected only a few genuine fingerprint pairs (Fig. 10), AFIS B rejected a relative huge number of genuine fingerprint pairs (threshold on level 20) on a whole time scale pairs (Fig. 11). We believe that the AFIS B system performed much worse than AFIS A mostly due to the lower quality of the fingerprint image processing, especially for the fingerprints of elderly people. The matching scores have a higher dispersion and lower distinctions among them. But still, almost all regression lines of the AFIS B matching scores have obvious downward trend.

6 Discussion

Although our study unfortunately did not deal with AFISs similarity matching scores of fingerprints pairs recorded over a span of 21 years, based on results of the regression lines and the predefined threshold matching score lines in Figure 9, we can predict that after approximately 30 year lapses between fingerprint recordings (the intersection of the regression lines and the AFIS A predefined threshold matching score), False–Recognition–Rate (FRR) will increase to 50%. Such results show higher FRR degradation, caused by template aging, than results in the previous research (Wilson et al., 2003). Based on their conclusions, where FRR doubles in 10 years' time lapses, AFIS A with FRR = 1% should have only 8% FRR after 30 years. Our results are more similar to results published in the paper (Yoon & Jain, 2015), which were obtained on a large database over a span of 12 years, but not treating each finger separately, as we have done in our study.

During testing with the AFIS A, we noticed that the good quality of both fingerprint images involved in the matching process does not guarantee a high matching score, but a very poor image quality of one or both fingerprint images always leads to a poor score. We also observed a constant decline of the AFIS A matching scores in relation to a person's aging, regardless of the quality level of fingerprint images measured by the MITRE's program IQF that have not shown a detectable downward trend (see Figure 6). Based on these observations, we presume that the majority of the AFISs matching scores variability could be explained just with the image quality of fingerprint images, and that only the minor part with the other factors as the fingerprint distortions, environmental characteristics, and of course with the template aging (approx. 9 %) that this paper investigated.

Referring to the regression lines in Figures 9 and 10, we can predict that in the interval between enrolment and recognition phases of 10 years (in many EU countries this is the maximum validity time period of biometric travel document for adult persons), an average decrease of a state of the art minutiae-based AFIS similarity matching scores for approximately 26% for the index finger of the right hand and approximately 23% for the index finger of the left hand. In spite of the fact that due to the template aging the AFIS similarity matching scores decrease, with reference to regression and decision threshold lines in Figures 9 and 10, for white males younger than 53 years, we do not expect any increase of a state of the art minutiae-based AFIS False-Recognition-Rate for templates up to 10 years old.

Referring to Figures 10 and 11, we notice that the template aging differences among fingerprints of all fingers of one hand and also differences of the same fingers between both hands. The regression lines of the matching similarity scores of fingerprints of the left thumb, index, and middle fingers are almost the same, but the regression lines of the right thumb, index, and middle fingers show significant diversity (AFIS A). Assuming that, on average, people are more right-handed, these changes are probably a consequence of the increased physical strain on the fingers of the right hand, which can cause greater permanent changes to the skin surface on fingerprints and thus greater template aging. Interestingly, similar fingerprint matching-score diversities of the index finger of the right and left hand were obtained in study (Schuckers & Lopez, 2005) on 6000 individuals over a three-year period, collected in a NIST database, where the slope of the fingerprint matching score regression line of the index finger of the left hand did not change (zero slope) in three years, but the fingerprint matching score regression line of the index finger of the right hand slightly declined.

7 Conclusion

Despite the relatively small number of people in our study, the statistical analysis of the matching results among the fingerprints obtained for different time intervals clearly confirms our prediction that the human body and, of course, also fingerprints, change with aging. These changes do not significantly affect the patterns of the fingerprints, but rather the small features at level II (minutiae). This study raises again the issue about the FBI expert assumptions (Budowle et al., 2006) that there is no need for further investigations on fingerprint changes at level II. As we have shown (see results of experiment I.), these changes are statistically significant even for a relative young population, and in consequence have a (limited) negative impact on the minutiae-based AFISs.

Our research was conducted on a relative young population, where the effects of a person's aging on fingerprint quality were really minor. For an older population (> 60 years) and for certain ethnic groups with a lower fingerprint quality (Spinella, 2003), the reliability of the minutiae-based AFISs due to the template aging can be questioned. Because most of the AFISs that are common in the services of Police and Border control authorities are minutiae–based (Maltoni et al., 2009), and especially with consideration of the constant trend of aging population, a decline in the performance of the minutiae-based AFISs can be anticipated, so we propose more comprehensive template aging investigations on an older-population data set.

Our research showed different impacts of the template aging on fingerprints of different fingers and even different impacts of the template aging on fingerprints of the same fingers of the right and left hand. It can also be observed an apparent diversity of the fingerprints matching scores scatters of the right hand fingers, especially of the thumb; therefore we recommend further investigations into the correlation between template aging and the person's handedness (right, left), too.

Acknowledgment

The authors would like to express their gratitude to the Slovenian National Forensic Laboratory for the utilization of resources and expert assistance as well as to Prof. Slobodan Ribarić (University of Zagreb, Croatia) for helpful discussions and suggestions.

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Revija za kriminalistiko in kriminologijo / Ljubljana 67 / 2016 / 4, 371–388

Vpliv staranja predlog prstnih odtisov na delovanje sistemov za samodejno razpoznavanje prstnih odtisov

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Na splošno velja prepričanje, da se prstni odtisi s starostjo bistveno ne spreminjajo, kar potrjuje tudi dolgoletna praksa uporabe prstnih odtisov za ugotavljanje in potrjevanje identitete neznanih oseb, saj te postopke policija uspešno uporablja že več kot stoletje. Vendar so se v preteklosti postopki ugotavljanja in potrjevanja identitete neznanih oseb na podlagi prstnih odtisov izvajali predvsem s pomočjo daktiloskopskih strokovnjakov. Z vse hitrejšim razvojem biometričnih naprav in uvedbo biometričnih dokumentov pa se dandanes sistemi za samodejno razpoznavanje prstnih odtisov uveljavljajo na različnih področjih vsakdanjega življenja. Pri tem se postavlja vprašanje, ali imajo prstni odtisi dovolj dobro dolgoročno stabilnost za zanesljivo delovanje sistemov za samodejno razpoznavanje prstnih odtisov (AFIS), kjer lahko časovni razmiki med posameznimi odvzemi prstnih odtisov iste osebe trajajo tudi desetletje in več? V prispevku se osredotočamo na ugotavljanje vplivov sprememb prstnih odtisov na delovanje sistemov za samodejno ugotavljanje in potrjevanje identitete neznanih oseb zaradi staranja predlog prstnih odtisov. Na podlagi statistične analize rezultatov ujemanja (AFIS) parov prstnih odtisov vseh prstov tako desne kot leve roke z dolžino časovnih razmikov med odvzemi tudi do 21 let, smo ugotovili, da kljub temu, da lahko v povprečju na račun staranja predlog pojasnimo samo 9 % variance rezultatov ujemanja, ima staranje predlog prstnih odtisov statistično pomemben negativen vpliv na uspešno delovanje sistemov za samodejno razpoznavanje prstnih odtisov, celo na vzorcu relativno mlade moške populacije, kjer se gibljejo njihove starosti med 14 in 53 leti.

Ključne besede: staranje predlog, razpoznavanje prstnih odtisov, samodejno razpoznavanje prstnih odtisov, stalnost prstnih odtisov

UDK: 343.98