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Masterthesis

Oliver Kühn

System requirements analysis of correlation-based algorithms for partial fingerprints in an embedded environment

Fakultät Technik und Informatik
Department Informations- und Elektrotechnik

Faculty of Engineering and Computer Science
Department of Information and Electrical Engineering

Oliver Kühn

System requirements analysis of correlation-based algorithms for partial fingerprints in an embedded environment

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Betreuender Prüfer : Prof. Dr. Heike Neumann
Zweitgutachter : Thomas Suwald (extern)

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System requirements analysis of correlation-based algorithms for partial fingerprints in an embedded environment

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Biometrics, fingerprint recognition, correlation, image processing

Abstract

This thesis documents the system requirements analysis of a fingerprint verification system that deals with limited information due to a decrease of the sensor capturing area. Basic parameters of correlation-based matching are identified and examined through biometric tests in a specifically developed environment. The results are evaluated with regard to the biometric performance as well as the required computational power on an ARM Cortex M4 architecture.

Thema der Masterthesis

Systemanforderungsanalyse von korrelationsbasierten Algorithmen für partielle Fingerabdrücke in einem eingebetteten System

Stichworte

Biometrie, Fingerabdruckerkennung, Korrelation, Bildverarbeitung

Kurzzusammenfassung

Diese Thesis dokumentiert die Systemanforderungsanalyse eines Fingerabdruck-Verifikationssystems, das aufgrund der Verkleinerung der Sensorfläche mit einer eingeschränkten Menge an Information arbeitet. Grundlegende Parameter des korrelationsbasierten Matchings werden identifiziert und mittels biometrischer Tests in einer eigens entwickelten Umgebung untersucht. Die Evaluation der Ergebniss erfolgt hinsichtlich der biometrischen Performance sowie des benötigten Rechenaufwandes auf einer ARM Cortex M4 Architektur.

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Hamburg, 17. März 2021

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List of abbreviations

C-OP	Correlation Operation 40
CAE	Correlation Analysis Environment 50
COG	Center Of Gravity 68
CPU	Central Processing Unit 84
DET	Detection-Error Tradeoff 21
EER	Equal-Error Rate 22
FAR	False Acceptance Rate 19
FMR	False Match Rate 19
FNMR	False Non-Match Rate 19
FRR	False Rejection Rate 19
FTIR	Frustrated Total Internal Reflection 25
FVC	Fingerprint Verification Competition 32
IDE	Integrated Development Environment 33
IoT	Internet Of Things 41
MCU	Microcontroller Unit 74
PIN	Personal Identification Number 23
SSD	Sum Of Squared Differences 37

1 Introduction

Please take a look at the fingerprint of your index finger. Have you ever considered the regularity of the fine lines? Have you ever noticed the small irregularities within the regular pattern?

Fingerprints are widely used to prove an individual's identity. The applications that utilize fingerprints range from security-critical ones to ones with a convenience background. A quick touch of the fingertip, and the individual is recognized. This principle would be helpful and practical in many different situations. How often must a password or token be provided before access to a service or facility is granted? A high security standard that implies the recognition of one individual among all individuals is often not necessary. Furthermore, this is also not guaranteed with weak passwords or transferable tokens.

Let us think about the following use case. Fingerprints can be utilized to enable a convenient assignment of something within a small group of people, for instance some friends, family or the residents of an apartment house. The attitude of sharing in a modern and resource-conscious society can reveal many new applications for fingerprint recognition.
A possible use case can be inside a car that is shared by lots of different parties. The fingerprint authentication can be convenient for assigning some configurations to the car, for example concerning the ergonomics or the entertainment system. This can be extended to purchasable modules, which are unlocked by the car's software when an entitled individual presents their fingerprint.
Another example would be a room of shared use in the basement of an apartment house. Something in this room is only available to residents of the house who are registered for it. That can be for example bikes or gym equipment. The access to the room is managed by fingerprint recognition. This has the advantage that no keys or other tokens are required. A registration or termination process can be handled easily. In addition, fingerprints cannot be passed to unauthorized individuals. In case of keys, this can be probable if the residents know each other.

Such applications require a compact solution that can be integrated into large environments. Even more flexibility is provided by a battery powered solution. A possible realization is a device that includes a fingerprint sensor and a microcontroller.

The recognition process comprises the capturing of a presented fingerprint, the comparison with a previously captured image of the fingerprint and the decision whether access is granted or denied.

However, such a device comes along with some technical challenges:

- Computational power and memory available are restricted on a microcontroller. In addition, the comparison of the fingerprints requires image processing, which is a computationally intensive operation per se.
- For a versatile utilization, the device must be small and compact. The size of the fingerprint sensor determines the size of the device. Furthermore, the sensor accounts for most of the cost. Reducing the sensor size can solve these issues, but it reduces the amount of information for the fingerprint recognition.
- The fingerprints for comparison must be securely stored on the device to prevent identity-fraud.

This project targets the first two challenges with a system requirements analysis of a fingerprint recognition system under limited information and restricted computational power. The reduction of the sensor size and the implementation on a microcontroller is investigated in order to find the boundaries of a reliable recognition. The associated conditions as well as the conceptual formulation are described in chapter 3. Before that, an introduction to the theoretical background is given in chapter 2. Chapter 4 describes the state of the art of fingerprint recognition with regard to this project. The conception of the analysis and the associated development activities can be found in chapter 5 and 6. The system requirements analysis is documented in chapter 7, 8 and 9, followed by the conclusion and an outlook in chapter 10 and 11.

Please note:

In addition to this thesis, the documentation of this project includes a number of external files on the CD attached. A detailed description of the electronic appendix can be found in appendix A. Throughout the thesis, these files are referred to as external PowerPoint files, Excel files or database files. This comprises an implicit reference to the given appendix section.

All figures in this thesis without source were created by the author as part of this project.

2 Theoretical background

The following chapter provides an introduction to the topic biometric recognition using fingerprints. Section 2.1 gives an overview about biometrics in general, followed by section 2.2, which describes the fingerprint as a biometric characteristic.

2.1 Biometric recognition

Biometrics is a collective term for the utilization of anatomical and behavioral characteristics of the human body for automatically recognizing individuals. Typical characteristics are for instance fingerprint, face, voice, iris and hand geometry. The term biometrics itself is derived from the Greek words *bio* (life) and *metron* (measurement). [Mal+09, p.2]

2.1.1 Biometric systems

This subsection is correspondingly based on [Mal+09, p.3 ff.].

The operation of a biometric system can be broken down into three main processes, namely, *enrollment*, *verification* and *identification*.

- An enrollment process is the initial registration. An individual is registered in the storage of the biometric system. The stored characteristic is called an *enrollment template*.
- In an identification process an individual does not explicitly claim an identity. Their biometric characteristic is compared against all enrolled templates in the data storage. This process conducts a one-to-many comparison.
- In a verification process an individual claims an identity. Their biometric characteristic is only compared against their enrolled template in the data storage. This process conducts a one-to-one comparison.

The processes are visualized in the following figure 2.1.

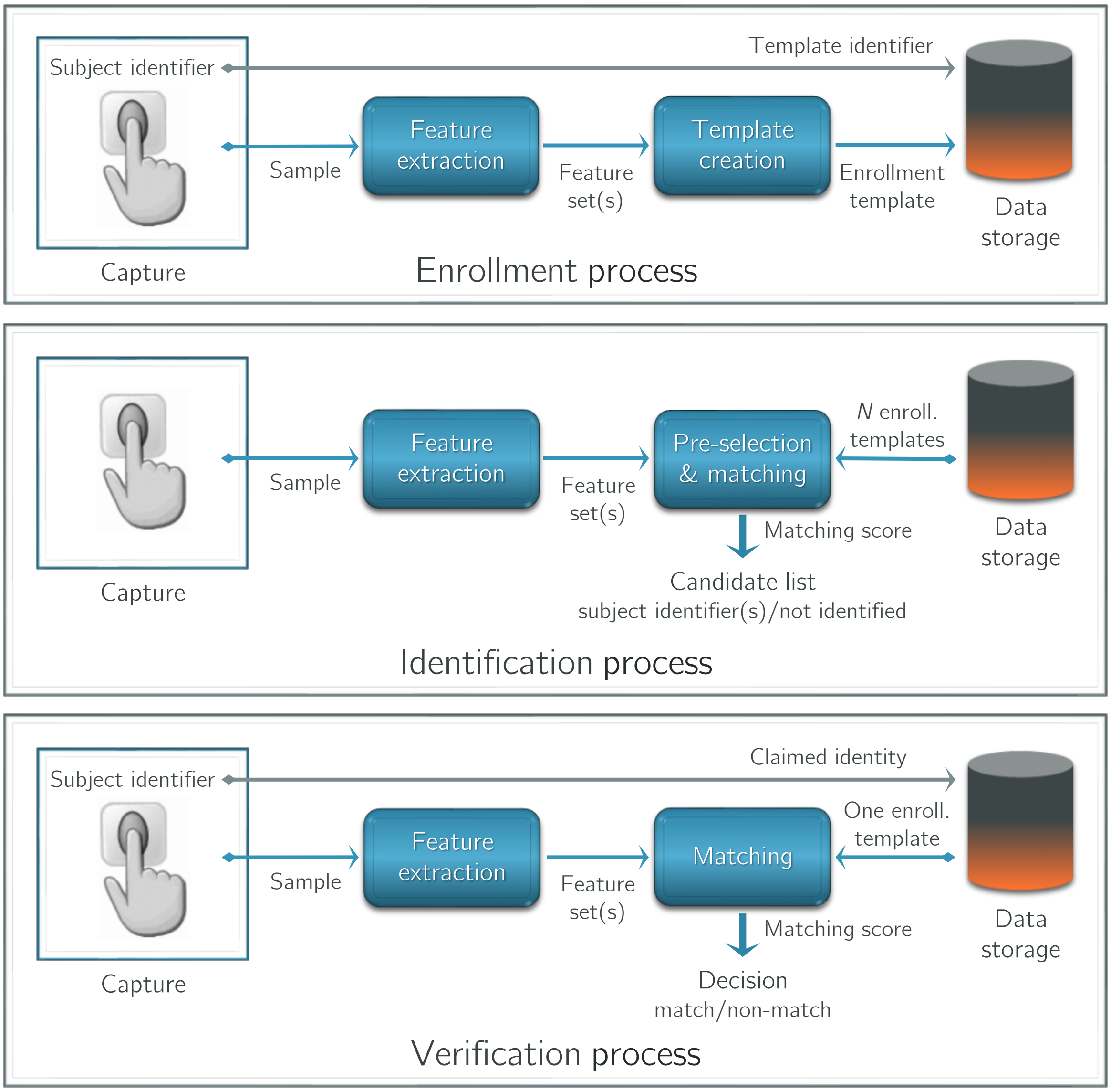

Figure 2.1: Enrollment, identification and verification process, based on [Mal+09, p.4]

Depending on the application context, biometric systems implement an identification or a verification process. Hence, these systems may be referred to as either an identification or a verification system. Both system types require an initial enrollment process.

Identification and verification systems can be structured into system modules that implement the main parts of the different processes. These modules are shown in figure 2.1 and briefly explained in the following:

- Capture:
  This module describes sensing and capturing of a digital representation of the biometric characteristic. The captured characteristic is referred to as a *sample*. The capturing may also include other (non-biometric) data.
- Feature extraction:
  This module describes the further processing of the sample in order to facilitate the comparison. The generated compact but expressive impression is called a *feature set*.
- Template creation:
  This module describes the creation of an enrollment template from one or more feature sets.
- Pre-selection (only for identification systems):
  This module describes an optional filtering or classification step before matching. That reduces the effective size of the template database in an identification process.
- Matching:
  This module describes the comparison (*matching*) of feature set and enrollment template. The similarity between them is computed in terms of a *matching score*. This score is compared to a defined threshold in order to make the final decision as to whether *match* or *non-match*.
- Data storage:
  This module describes the storage of templates and other information of the individuals.

Identification and verification processes differ in terms of their output. An identification process conducts a one-to-many comparison. Output is a *candidate list*, which contains the identifiers of all enrollment templates that match with the current feature set. If no match occurred, this list is empty. In figure 2.1 an empty candidate list is illustrated by »not identified«. A verification process conducts a one-to-one comparison. The output corresponds to the decision, match or non-match.

An example for a verification process is a contactless payment using a bank card with an integrated fingerprint sensor. By presenting the card to the base-station, the individual claims an identity. In order to prove whether the card presenter is the card owner, a fingerprint is captured. The captured sample goes through the feature extraction module and is compared against the pre-saved template. If the algorithm on the card decides for a match, the identity of the individual is confirmed and the payment is authorized towards the point of sale.

An example for an identification process is an access system based on a fingerprint recognition. The individual presents their finger directly without providing any other information of their identity. The captured sample goes through the feature extraction block and is matched against all templates of the database. An optional pre-selection step classifies the feature set in order to reduce the number of comparisons. Access is granted if the matching process succeeds at least once.

This project addresses only the verification case with the one-to-one comparison mode.

2.1.2 Performance of biometric verification systems

Error rates and charts to evaluate the performance of a biometric verification system are explained below. The impact of the test size on the error rates is described afterwards.

Error rates

This part is correspondingly based on [Mal+09, p.14 ff.].

On a high abstraction level, the two parts of the one-to-one-comparison in a verification process can be referred to as *reference* and *input*. The reference is the enrolled template in the data storage. The input is the biometric characteristic just captured.

There are two possible hypotheses:

- H_0: The input does not come from the same individual as the reference.
- H_1: The input comes from the same individual as the reference.

Furthermore, there are two possible associated decisions:

- D_0: Non-match
- D_1: Match

Corresponding to the hypotheses and the decisions, there are two types of errors:

- False match
  - D_1 is decided when H_0 is true.
- False non-match
  - D_0 is decided when H_1 is true.

The probabilities of these errors are the corresponding error rates:

- False match rate
  - $FMR = P(D_1|H_0)$
- False non-match rate
  - $FNMR = P(D_0|H_1)$

FMR and FNMR are error rates of the matching module in one-to-one comparison mode. With respect to the entire verification process, two other error rates are more common and will be used throughout this thesis:

- FAR: False acceptance rate
- FRR: False rejection rate

Their exact meaning is dependent upon the type of biometric *claim*[1] made by the individual. The meaning of the terms acceptance and rejection also depends on that. For example, in a border control, »accepting« means to be not an enrolled subject. Transit is possibly rejected in case of a match. On the other hand, for the previous example of a contactless payment, »accepting« means to be an enrolled subject. The payment is authorized in case of a match.

In this project only the *specific positive claim*[2] is the scenario of interest. This corresponds to the contactless payment example. Consequently, the error rates are defined as:

- $FAR = FMR$
- $FRR = FNMR$

[1] Biometric claim as defined in [Mal+09, p.6]: »*A biometric claim (or claim of identity) is defined as the implicit or explicit claim that a subject is or is not the source of an specified or unspecified biometric enrollment template.*«

[2] The individual is enrolled as a specified biometric enrollee, [Mal+09, p.7]

The accuracy of a biometric system can be evaluated by collecting scores generated from a large number of comparisons. These matching scores can be parted into two distributions:

- Genuine distribution
    - Scores of comparisons between reference and input from the same individual
- Impostor distribution
    - Scores of comparisons between reference and input from different individuals

In the same way, the terms *genuine* and *impostor* are used throughout the thesis to refer to the relation of input and reference.

The matching score is compared with the *system threshold* in order to meet the final decision, match or non-match.

- t: System threshold

If the score is greater than or equal to the threshold the decision is match. Otherwise it is non-match. Figure 2.2 illustrates the computation of FAR and FRR over the distributions for a given threshold.

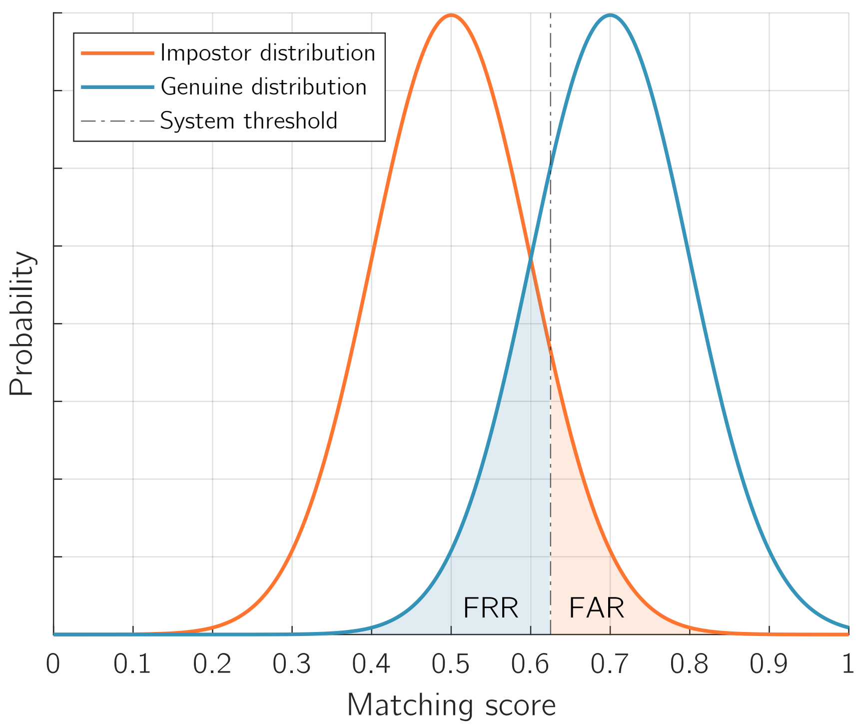

Figure 2.2: Distribution chart, $t = 0.625$

The probability, which is the number of matching scores divided by the total number of impostor respectively genuine comparisons, is plotted against the matching score. This chart can also be used to evaluate the discriminability between genuine and impostor comparisons. The further apart the maxima of the distributions, the better is the entire system performance. The error rates defined by the overlapping area are thus decreased. Throughout the thesis this chart is called *distribution chart*.

Both error rates are functions of the system threshold. Therefore the following denotations are more correct:

- $FAR(t)$
- $FRR(t)$

There is a strict tradeoff between these two error rates in every biometric system. Decreasing the threshold makes the system more tolerant against input variations and noise. Consequently, the system is less secure but more user convenient due to a less number of false rejections. Increasing the threshold makes the system more secure but less convenient to the user. The error rates evolves as follows:

- Decrease of t
  - $FAR(t)$ increases
  - $FRR(t)$ decreases
- Increase of t
  - $FAR(t)$ decreases
  - $FRR(t)$ increases

The evaluation of the system performance is advisable at all operating points, which are defined by the system threshold. Hence, each operating point consists of a pair of FRR and FAR. The DET[3] curve is a plot of FAR against FRR for all operating points. An example is shown in figure 2.3. The closer the curve to the lower left corner, the better is the entire system performance.

[3]DET - **D**etection-**E**rror **T**radeoff

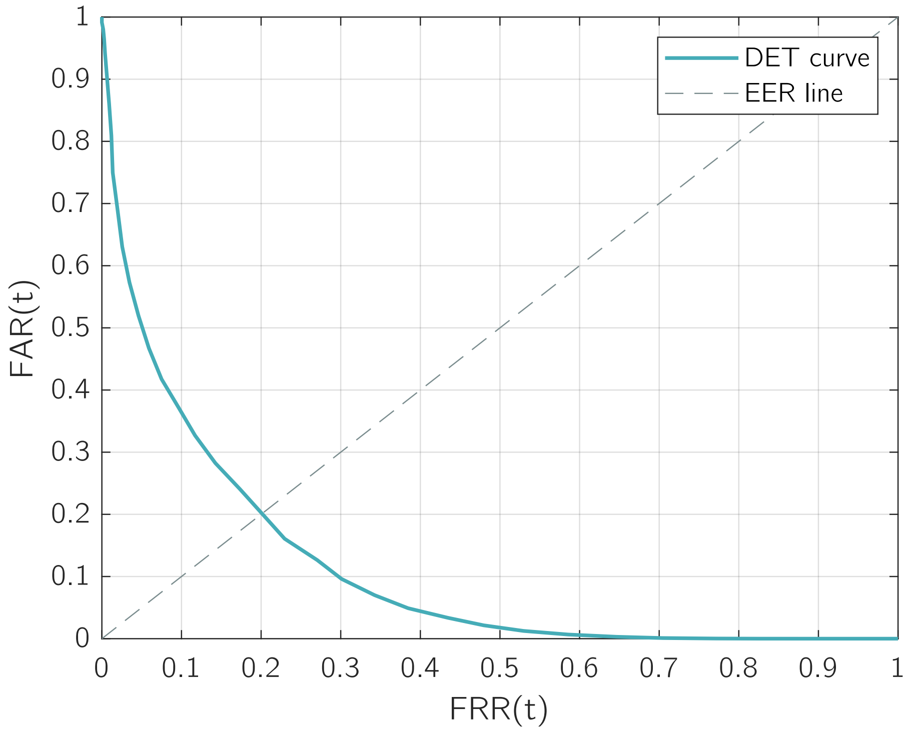

Figure 2.3: DET chart

The intersection with the angle bisector shows the point where FAR is equal to FRR. This operating point, called EER[4], is commonly used as a compact parameter to describe the performance of a verification system.

The plots shown in figure 2.2 and 2.3 as well as the EER will be used throughout this thesis to evaluate the biometric performance.

Test size

This part is correspondingly based on [MW02, p.15 f.].

The goal of a performance test is the understanding and predicting of the error rates of a biometric system when applied to the entire population. A test group of individuals provides only a limited variance of the biometric characteristic. Consequently, the accuracy of the determined error rates is dependent on the number of individuals and the number of comparisons made. The larger the test group, the more accurate the error rates are likely to be.

[4] EER - **E**qual-**E**rror **R**ate

Lower bounds for the needed number of comparisons for a certain level of accuracy are given by the »Rule of 30«. The rule gives a minimum number of errors in order to be 90% confident that the true error is within an error band of the observed value:

- 11 errors
  - True error rate is within ±50 % of the observed value.
- 30 errors
  - True error rate is within ±30 % of the observed value.
- 260 errors
  - True error rate is within ±10 % of the observed value.

For example, an FAR test that comprises 30 errors in 10,000 impostor comparisons:

$$FAR_{obs} = 0.03\,\%$$

$$FAR_{true} = FAR_{obs} \pm 30\,\% = [\,0.021\,\%, 0.039\,\%\,]$$

Another example would be an FAR that corresponds to a 4-digit PIN[5]. In order to determine the true error rate within an error band of 10%, the number of comparisons must be at least

$$N = \frac{n_{Errors}}{FAR_{PIN}} = \frac{260}{0.01\,\%} = 2{,}600{,}000 \quad .$$

These examples reveal the need for a large test group. The error with single comparisons are not a valid measure of the biometric performance.

A performance test of a verification system, as described in this section, is called a *biometric test* throughout the thesis. Each of these tests includes an number of comparisons that enables the significance of the error rates. The result evaluation afterwards is carried out in terms of the distribution chart, the DET chart and the EER.

[5] PIN - **P**ersonal **I**dentification **N**umber

2.2 Fingerprint recognition

The analysis of fingerprint structures as a method for recognition goes back over 100 years. Today fingerprints are a widely deployed biometric characteristic. This is due to the history of forensics and law enforcement. More recently, fingerprints and also other biometric technologies are increasingly utilized in a large number of non-forensic applications, e.g. unlocking of smart devices. [Mal+09, p.1 f.]

Another reason for its suitability as a biometric characteristic is the uniqueness and the consistency of the fingerprint. The structural pattern on each finger of every person is considered unique. The consistency of fingerprints has been proven based on the anatomy and morphogenesis of friction ridge skin. Thus, the individuality of fingerprints is empirically accepted. [PPJ02]

2.2.1 The fingerprint as a biometric characteristic

This subsection is correspondingly based on [Mal+09, p.38 ff.].

Fingerprints are composed of *ridges* and *valleys*. These structures are fully formed before birth and normally do not change throughout life. However, heavy workload for hands as well as cuts and bruises because of accidents may change parts of the fingerprint. Figure 2.4 shows the captured ridge-valley structure of a fingerprint. Ridges are normally illustrated black whereas valleys are illustrated white.

Figure 2.4: Example of a captured fingerprint, based on [Mai+02a, DB2]

Based on the mode of acquisition, fingerprint images may be classified as *off-line* or *live-scan*. An off-line image is obtained by ink and paper and digitized afterwards. A live-scan image is obtained by using a sensor that is capable of digitizing the fingerprint directly on contact. Typical live scan sensing mechanisms are e.g. optical FTIR[6], capacitive, thermal, pressure-based or ultrasound. For further information about sensing technologies please be referred to [Mal+09, p.57 ff.].

The capturing is followed by the feature extraction. A pixel intensity value in a fingerprint image is not invariant over time of capture. Consequently, there is a need for salient, time invariant features. These features should enable, on the one hand, to discriminate between different fingers and, on the other hand, to recognize impressions of the corresponding finger. One differs between *intra-class variations* and *inter-class variations*:

- Intra-class variations
    - Variations within different captured images of the same finger
- Inter-class variations
    - Variations between captured images of different fingers

A desired fingerprint representation defines a feature space with low intra-class and high inter-class variations. The main factors that cause problematic intra-class variations are listed below:

- Displacement
- Rotation
- Partial overlap
- Non-linear distortion due to variable fingertip pressure during capturing
- Changing skin condition
- Sensor noise

Next to the saliency of the fingerprint representation, the suitability for easy extracting, storability in a compact fashion and utility for matching are important properties. A salient representation does not necessarily mean a suitability for automatic recognition.

[6] FTIR - **F**rustrated-**T**otal **I**nternal **R**eflection

Fingerprint patterns exhibit various features when analyzed at different scales. A distinction is made for three levels:

- Level 1 – Global features:
  At a global level, the ridge flow patterns make a definition of structure types possible. Examples of some types are shown in figure 2.5. Singular points, called loop and delta, are marked in orange. Global features are useful for classification and indexing. However, for matching purposes, the feature distinctiveness in the coarse structure is not sufficient.

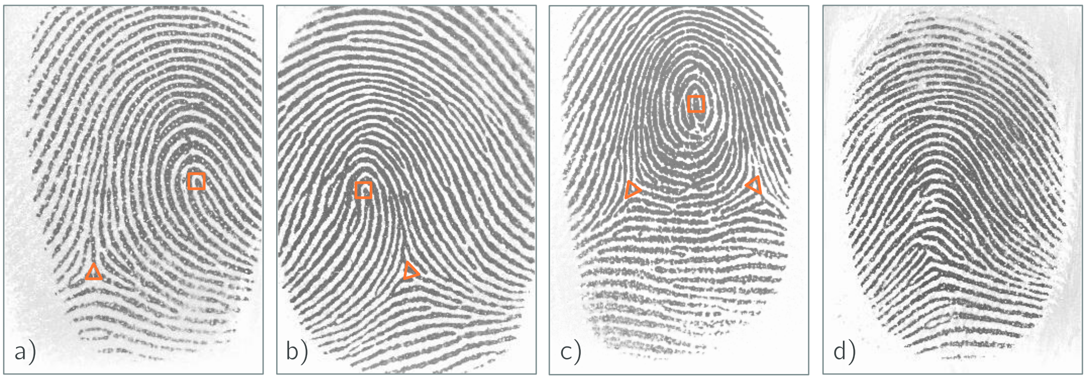

Figure 2.5: Examples for fingerprint types, a) left loop, b) right loop, c) whorl, d) arch with singular points (square – loop type, triangle – delta type), based on [Mai+02a, DB2]

- Level 2 – Local features:
  At a local level, an analysis of the local ridge characteristics, so-called minute details, is possible. Over 150 various types have been identified, but only two of them are stable and robust to fingerprint impression conditions. These so-called *minutiae* are ridge endings and ridge bifurcations. An overview of commonly occurring ridge characteristics is shown in figure 2.6.

- Level 3 – Intra-ridge features:
  At a very fine level, an extraction of characteristics within a ridge is possible. This includes width, shape, curvature and edge contours of a ridge. Furthermore, sweat pores inside a ridge or narrow incipient ridges can be features. The reliable extraction of these details requires a high resolution capturing in good quality. This is usually not practical in a commercial non-forensic application. Sweat pores are shown in figure 2.6.

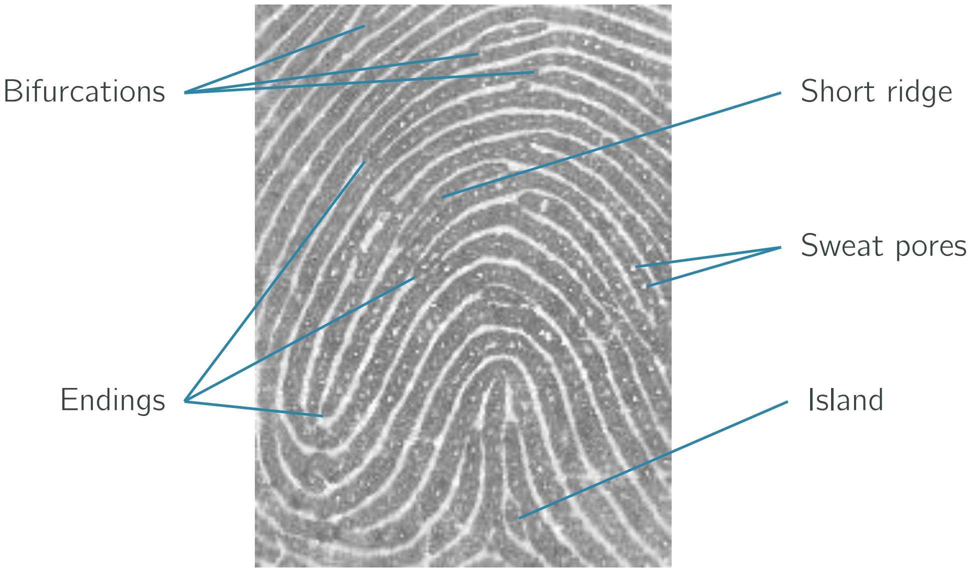

Figure 2.6: Level 2 & 3 features, based on [Mai+02a, DB2]

Due to feature extraction errors because of intra-class variability, reliable matching of fingerprints is a sophisticated challenge. The design of a matching algorithm needs to characterize a realistic model of the expected variations among the representation of mated pairs.

Approaches of fingerprint recognition can be coarsely classified into the following three categories:

- Minutiae-based recognition
- Non-minutiae feature-based recognition
- Correlation-based recognition

These categories are briefly explained in the following sections.

2.2.2 Minutiae-based recognition

This subsection is correspondingly based on [Mal+09, p.97 ff.].

Minutiae-based recognition is the most common approach due to its history in forensics. The following procedure summarizes the feature extraction process in its most common way used for automatic applications:

- Directional field estimation and adaptive noise filtering
- Enhancement, binarization and thinning[7]
- Minutiae extraction and filtering

After different pre-processing steps, the minutiae are extracted from the captured image and saved as feature vectors. A post-processing stage is used to filter spurious minutiae.

The exact definition of the feature vector depends on the matching algorithm. Mostly, a single minutia is characterized by location and orientation. In this case, two minutiae are considered »matching« if the spatial distance as well as the direction difference between them is smaller than a defined tolerance. A final decision is met after finding the alignment that results in the maximum number of minutiae pairings.

A minimum of 12 minutiae is considered as a sufficient evidence in many courts of law for a proof of identity. This is referred to as the *12-point guideline*.

The main drawback of minutiae-based algorithms is the handling of bad-quality fingerprints. Missing some minutiae and extracting some spurious minutiae leads to errors in the matching stage. Furthermore, partial fingerprints may not contain enough minutiae to ensure a reliable recognition.

2.2.3 Non minutiae-based recognition

This subsection is correspondingly based on [Mal+09, p.216 ff.].

The use of non minutiae-based features is often an alternative or supplement to minutiae-based approaches. Examples for non minutiae-based feature are:

- Size of the fingerprint and shape of the external fingerprint silhouette
- Number, type and position of singularities

[7] The process in which each ridge breadth is thinned to one pixel.

- Global and local texture information
  - Spatial repetition of basic elements, characterized by properties such as scale, orientation, frequency, symmetry etc.
- Geometrical attributes and spatial relationship of the ridge lines
- Level 3 features (e.g. sweat pores)

The extraction of these features may be more reliable in low-quality fingerprint images even though their distinctiveness is generally lower than that of minutiae.

2.2.4 Correlation-based recognition

This subsection is correspondingly based on [Mal+09, p.172 ff.].

Correlation-based approaches superimpose the input on the reference and compute the distance between the corresponding pixels for different alignments. The result is a similarity measure for every alignment. This kind of approach is the investigation area of this project. A more extensive introduction to typical issues and existing approaches can be found in chapter 4.

There are both purely correlation-based approaches as well as combined ones with other features. For instance, the similarity of small regions surround minutiae can be used as an additional consolidation stage to assess the quality of a matched minutiae pair.

2.3 Collection of fingerprint images

The characteristics of fingerprint images, which are described in the previous section, are exemplified below.

Figure 2.7 shows four images of the same finger. The similarity is easy to recognize for the human eye. A comparison at pixel level is complicated by various factors. The different background and thus the difference in the valley intensities is disadvantageous. Furthermore, ridge intensity and breadth are different in each image. Non-linear distortion due to variable fingertip pressure is particularly noticeable above the loop of the image on the far right. The ridge thickness is clearly increased in comparison to the image next to it.

Figure 2.7: Fingerprint images from the same finger, based on [Mai+02a, DB2]

Figure 2.8 shows examples for not desired variability of an impostor comparison (a&b) and a genuine comparison (c&d). In addition, compared to the previous figure, this one reveals the general diversity that can appear with different capturing sensors, even if the two sensors belong to the same category of capacitance sensors.

Figure 2.8: a) & b) Fingerprint images from different fingers with low inter-class variability, c) & d) Fingerprint images from the same finger with high intra-class variability, based on [Mai+02b, DB3]

Figure 2.9 shows some examples for poor quality images.

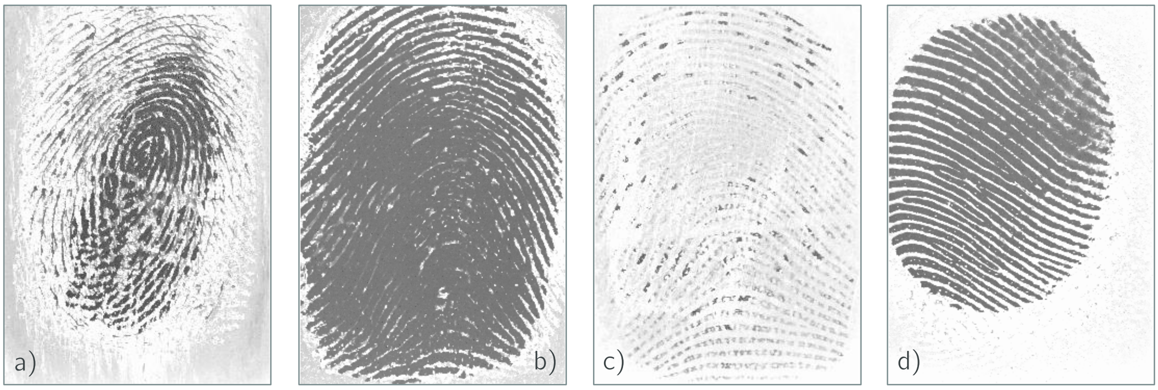

Figure 2.9: Fingerprint images with low quality, based on [Mai+02a, DB2]
a) Non-uniform fingertip pressure during capturing
b) Skin condition - high moisture
c) Skin condition - low moisture
d) Partial overlap

Some examples for scars and ceases in fingerprints are shown in Figure 2.10.

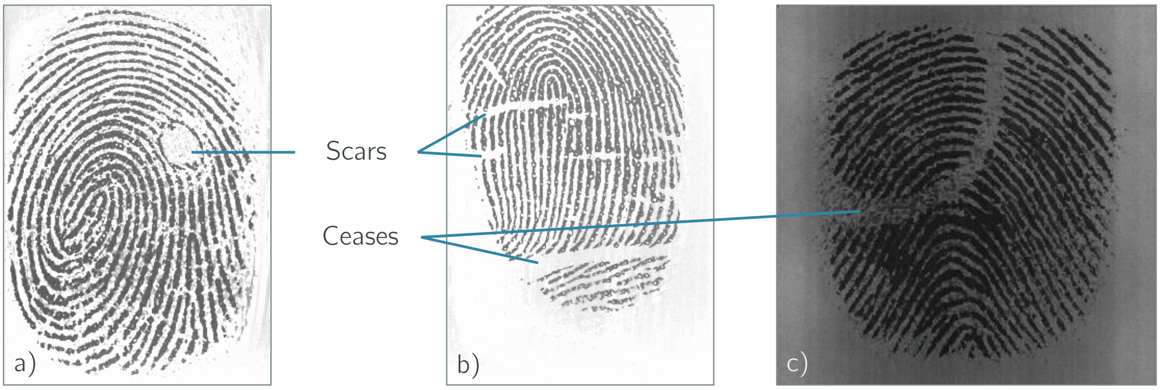

Figure 2.10: Fingerprint images with scars and ceases,
a) & b) based on [Mai+02a, DB2], c) based on [Mai+02b, DB3]

3 Analysis of the conceptual formulation

As mentioned in the introduction, a smaller fingerprint sensor leads to lower hardware costs and more compactness, but also to several technical challenges. The question arises as to whether fingerprint recognition can be carried out reliably when dealing with partial fingerprints and restricted computational power.
Partial fingerprints may contain far fewer minutiae than required to fulfill the 12-point guideline. This limitation of distinctive information creates a need for a different matching approach. The hosting company set the focus of this project to correlation-based approaches. Consequently, the information reduction results in features that are composed of image gray-scale values instead of minutiae.

A system requirements analysis must be carried out for a fingerprint verification system that uses correlation-based matching. This system must provide a reasonable biometric performance. The key parameters of correlation-based matching must be identified and investigated concerning their impact on biometric performance and computational effort. The determination of the best possible performance is not the goal of this project. The analysis must make a statement possible, which addresses the feasibility of correlation-based matching under the conditions of this project. Each of the following parameters describes one condition.

As mentioned in section 2.1.2, a biometric test requires a certain test size to measure the error rates with a certain statistical confidence. The hosting company set two databases of the FVC[8] as input for the analysis:

- FVC2000 DB2 - 880 images at 500 dpi resolution
- FVC2002 DB3 - 880 images at 500 dpi resolution

Section 4.4 provides more information about the databases and the contained fingerprint images. Regarding the enrollment and the verification process in figure 2.1, the capturing module in this project consists of processing the FVC images instead of capturing with hardware.

[8] FVC - **F**ingerprint **V**erification **C**ompetition

The impact of different sensor sizes is investigated by cropping the images. The following range of sensor capturing areas must be analyzed:

- 25 mm^2 to 50 mm^2

The impact of different sensor resolutions is investigated by scaling down the images. Upscaling would not result in a higher amount of information and is therefore of no interest. The following resolutions must be analyzed:

- 250 dpi, 375 dpi, 500 dpi

The target hardware architecture for the verification system is *ARM Cortex M4* with the following configuration:

- Clock rate: 96 MHz
- Available memory: 32 kB
- Programming language: C

There is no predetermined matching algorithm defined by the hosting company. A comprehensive research is recommended to obtain an overview about disclosed techniques.

Enrollment and verification must be implemented as separate parts of the algorithm. The verification process is time critical whereas the enrollment process is not. The following timing requirement is applied as an orientation:

- Maximum duration of a verification process: 1 s

The resources must be measured using the microcontroller *NXP LPCXpresso5411x*. Due to the home office guideline during this project, the measurement takes place inside the *MCUxpresso* IDE[9]. The analysis of the resources must be focused on the following parameter:

- Duration of a verification process
- Required memory for a verification process including the enrollment template

The conclusion of this project must include a statement to the question whether fingerprint recognition can be carried out under the described conditions. This must comprise a minimum sensor size together with the associated expected computational effort.

[9]IDE - **I**ntegrated **D**evelopment **E**nvironment

4 State of the art

The following chapter provides an overview about image matching using correlation and its state of the art concerning fingerprints. In section 4.1 the so-called template matching is described in general. This is described in particular when matching fingerprint images in section 4.2. Furthermore, section 4.3 outlines the carried out algorithm research and section 4.4 gives additional information about the FVC databases.

4.1 Template matching using correlation

Fingerprint recognition can be treated as a template matching problem. This section gives a general introduction to this topic when working with gray-scale images and correlation-based methods. It is correspondingly based on [BB16, p.565 ff.].

The basic questions arise as to when two images are considered as the same or similar and how this similarity can be measured. Two images are compared using the pixel information position and intensity. A series of effects complicates this comparison. Different lighting or different camera conditions might change the pixel values in a non-linear way. Furthermore, noise, quantization errors as well as minute shifts and rotations can create large numerical pixel differences, even if the pair of images are perceived as identical by a human viewer. Human perception incorporates a much wider concept of similarity including the recognition of structure and content. The challenge of comparing images at a structural or semantic level is a big field of research.

However, template matching describes a simpler problem of comparing images at the pixel level. A given sub-image[10], called *template*, has to be localized within some larger image. Positions with high similarity are obtained by shifting and rotating the template over the *search image* and measuring the difference. The essential questions are:

I What is a suitable difference measure?

II How can brightness and contrast changes be compensated?

III What total difference means a match?

[10]A subset of an image.

In the following, various distance functions are described together with first approaches to face these questions. For reasons of clarity and comprehensibility, rotation is not taken into account.

4.1.1 Problem definition

In order to answer the first question, the problem can be defined in the following way. A reference image (template) and a larger search image are given:

- R: Reference image
    - Dimension $M_R \times N_R$
    - Pixel coordinate (r, s)
- I: Search image
    - Dimension $M_I \times N_I$
    - Pixel coordinate (i, j)

The objective is to find the position where the similarity between the shifted template and the corresponding sub-image of the search image is a maximum. The amount of the shift is defined as *offset*, which corresponds to a pixel coordinate of the reference image:

- (r, s): Offset

Various measures of similarity for computing a distance between images have been proposed. The result of these measures is defined by the distance between the shifted template and corresponding sub-image of the search image for each offset:

- $d(r, s)$: Distance

Figure 4.1 on the next page illustrates the definition above. $R_{(r,s)}$ denotes the reference image shifted by an offset.

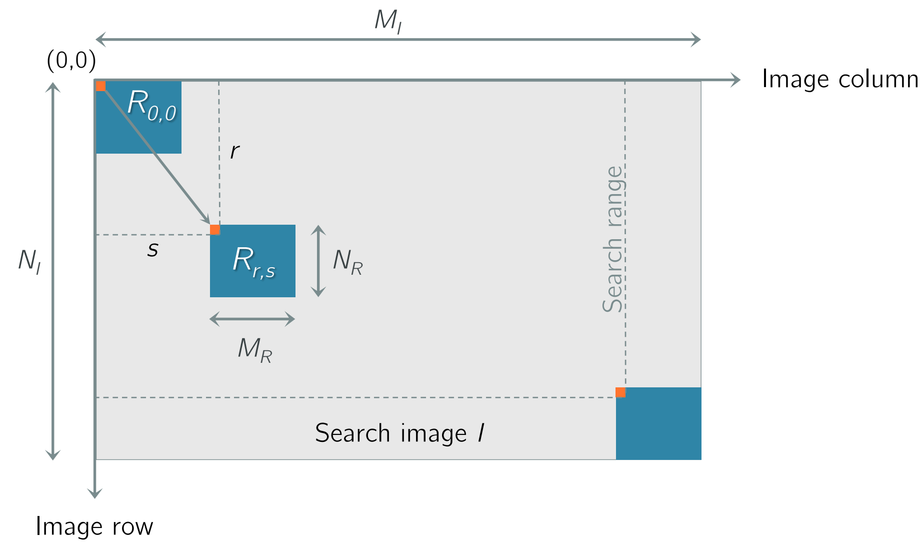

Figure 4.1: Definition - template matching, based on [BB16, p.566]

Figure 4.2 illustrates the distance computation for one offset.

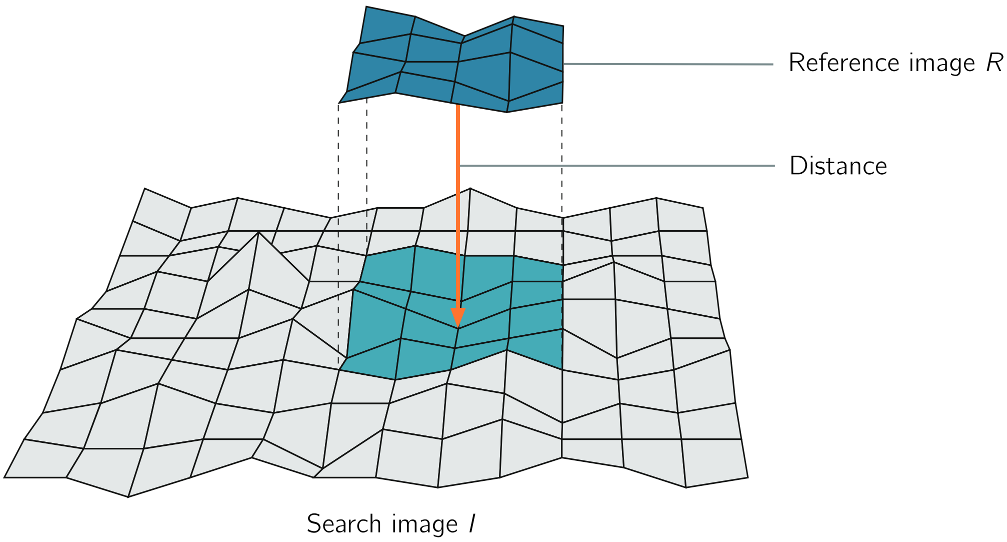

Figure 4.2: Distance computation for one offset, based on [BB16, p.566]

The computation is usually done pixelwise for each pixel of the template. The set of all possible template coordinates are specified by the following short notation:

- $\{(i, j) \in R \mid 0 \leq i < M_R,\ 0 \leq j < N_R\}$: Possible template coordinates
    - Short notation $(i, j) \in R$

4.1.2 Correlation-based distance measures

The *Euclidean distance*, a basic measure for distance, is shown in the following equation.

$$d_E(r,s) = \left[\sum_{(i,j)\in R} \Big(I(r+i, s+j) - R(i,j) \Big)^2 \right]^{1/2} \tag{4.1}$$

The best matching-position is defined by the minimum of the square of the Euclidean distance:

$$d_E^2(r,s) = \sum_{(i,j)\in R} \Big(I(r+i, s+j) - R(i,j) \Big)^2 \tag{4.2}$$

Equation (4.2) is also called sum Of squared differences (SSD). It can be expanded to

$$d_E^2(r,s) = \underbrace{\sum_{(i,j)\in R} I^2(r+i, s+j)}_{\text{A(r,s)}} + \underbrace{\sum_{(i,j)\in R} R^2(i,j)}_{\text{B(r,s)}} - 2 \cdot \underbrace{\sum_{(i,j)\in R} I(r+i, s+j) \cdot R(i,j)}_{\text{C(r,s)}} \quad . \tag{4.3}$$

The above equation can be parted into three terms:

- $A(r,s)$
  - Sum of squared values of the sub-image of I at offset (r,s)
- B
  - Sum of squared values of the template
- $C(r,s)$
  - Linear cross correlation between the sub-image of I at offset (r,s) and R

The linear cross correlation is generally defined as follows:

$$(I * R)(r,s) = \sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} I(r+i, s+j) \cdot R(i,j) \tag{4.4}$$

Assuming that the pixel values of both images are zero outside their boundaries, the equation results in

$$\sum_{i=0}^{M_R-1} \sum_{j=0}^{N_R-1} I(r+i, s+j) \cdot R(i,j) = \sum_{(i,j)\in R} I(r+i, s+j) \cdot R(i,j) \quad , \tag{4.5}$$

which is equivalent to the term $C(r,s)$ from equation (4.3).

The term B is the signal energy of the template. This is a constant value for all offsets and can therefore be ignored. The term A is the signal energy of the corresponding sub-image of the search image at the current offset. This term can only assumed as constant in an image with a high repetitive pattern and steady capturing conditions. In this case, the minimum distance can be found by computing only the maximum value of the correlation term C. Unfortunately, this assumption does not hold for most of the images. Consequently, the cross correlation strongly varies with intensity changes in the search image.

In order to overcome this dependency, the *normalized cross correlation* takes into account the terms A and B as follows:

$$\begin{aligned} C_N(r,s) &= \frac{C(r,s)}{\sqrt{A(r,s) \cdot B}} = \frac{C(r,s)}{\sqrt{A(r,s)} \cdot \sqrt{B}} \\ &= \frac{\sum_{(i,j)\in R} I(r+i, s+j) \cdot R(i,j)}{\left[\sum_{(i,j)\in R} I^2(r+i, s+j)\right]^{1/2} \cdot \left[\sum_{(i,j)\in R} R^2(i,j)\right]^{1/2}} \end{aligned} \tag{4.6}$$

The result of the normalized cross correlation is in the range $[0,1]$, whereby the following indications are given:

- Maximum agreement $C_N(r,s) = 1$
- Minimum agreement $C_N(r,s) = 0$

The expression in equation (4.6) compensates intensity changes within the search image. However, it measures the absolute distance. An altering of the overall intensity of the search image may also change the results dramatically. A solution to this problem is a comparison of the difference of pixel intensity values and average values.

The average value of the template and the corresponding sub-image of the search image are defined as follows:

$$\bar{R} = \frac{1}{M_I \cdot N_I} \cdot \sum_{(i,j)\in R} R(i,j) \tag{4.7}$$

$$\bar{I}_{r,s} = \frac{1}{M_I \cdot N_I} \cdot \sum_{(i,j)\in R} I(r+i, s+j) \tag{4.8}$$

This modification turns equation (4.6) into the so-called *correlation coefficient*:

$$C_L(r,s) = \frac{\sum_{(i,j)\in R}\big(I(r+i,s+j) - \bar{I}_{r,s}\big) \cdot \big(R(i,j) - \bar{R}\big)}{\Big[\sum_{(i,j)\in R}\big(I(r+i,s+j) - \bar{I}_{r,s}\big)^2\Big]^{1/2} \cdot \Big[\sum_{(i,j)\in R}\big(R(i,j) - \bar{R}\big)^2\Big]^{1/2}} \tag{4.9}$$

The result of the correlation coefficient is in the range $[-1, 1]$, whereby the following indications are given:

- Maximum agreement $C_L(r,s) = 1$
- Minimum agreement $C_L(r,s) = 0$
- Maximum disagreement $C_L(r,s) = -1$

The normalized cross correlation and the correlation coefficient provide first approaches to handle brightness and contrast changes, as indicated in the second question at the beginning of this section.

The third question was about the amount of agreement that indicates a match. The sum of squared differences and the Euclidean distance provide a score that is not normalized. The normalized cross correlation and the correlation coefficient have the advantage that they provide a matching score in a defined range. This can be used directly with a suitable threshold in order to decide about match or non-match.

If rotation is considered, the equations above are computed additionally for the search image rotated around its center. The angle of rotation defines the amount of rotation:

- φ: Angle of rotation

Please note that the matching score of the comparison is usually the highest score of a correlation map. The correlation map is defined as the entirety of scores for every offset of every rotation.

- $C(r, s, \varphi)$: Correlation map

The computation of a single score of the correlation map is referred to as a *correlation operation* (C-OP) in this project.

These are the definitions for the general case. There are a few differences when matching fingerprints, which are described in the following section.

4.2 Fingerprint matching using correlation

In the previous section, template matching is described as the determination of offset and angle with the highest agreement of a reference image within a larger search image. For fingerprint recognition, the scenario is reverse in terms of the image sizes. The entire finger is captured during the enrollment process to guarantee a certain amount of overlap with the single image captured during the verification process. Consequently, for fingerprint recognition, the reference is the larger search image. Usually the same sensor is used for enrollment and verification. For sensor sizes where partial fingerprints are captured, the enrollment template usually consists of several images. In this section, the terms are used as follows to distinguish the images:

- *Reference*
    - The image(s) captured during the enrollment process
- *Input*
    - The image captured during the verification process

The distance measures provide a matching score of the input within the reference. In addition to displacement and rotation, further intra-class variations, which are more difficult to handle, are mentioned in section 2.2.

Correlation-based approaches in particular suffer from these variations. The fingertip pressure may cause non-linear distortion. Due to non-uniform pressure, this can even be different in sub-regions of the same image. Moreover, based on the moisture of the skin, the captured fingerprints may have either thinner or thicker ridges. Additionally, the quality of the captured images may vary with time, which complicates the correlation process. [RRJ02]

However, algorithms of the fingerprint verification competitions demonstrated that these methods have been used successfully for fingerprint matching, [Lin+07]. Bazen stated that the gray-scale information in a fingerprint image contains much richer and more discriminatory information than only minutiae locations; merely a small part of the local ridge-valley structure is characterized by those locations, [Baz+00].

Different approaches for handling the intra-class variations have been examined. In order to provide an insight into their variance, some general considerations are described below in an exemplary way.
As mentioned before, particular distance measures can compensate contrast and brightness differences.
A pre-processing stage can prepare reference and input for matching. For instance, image normalization assures the use of the entire gray-scale range. Furthermore, a filtering stage can reduce artifacts from capturing like sensor noise.
The effect of non-linear distortion can be reduced by dividing the fingerprint images into smaller regions and computing the similarity on a local base, [ZBS14].

The best strategy depends on the target application and is a tradeoff between computational cost and biometric performance. Zanganeh stated that although correlation-based methods are more reliable than minutiae-based approaches, their main drawback is their computational cost, [ZBS14].
By computing the score of every possible displacement and rotation, the best alignment can be found with certainty. However, this leads to a significant increase in the number of correlation operations during the normally time-critical verification process. The key to reducing this number is to find the best alignment without computing every score. This can be done by using other features of the fingerprint for a pre-alignment, for example singular points or minutiae. Another approach to reduce the time for a verification process may be the execution of computational expensive operations during the enrollment process.

The design of a correlation-based matching algorithm involves many degrees of freedom. This is due to the diverse target applications and their circumstances. For example, fingerprint recognition can be implemented as part of an IoT[11] application with restricted resources as well as on a smart phone with a multi-core environment. Moreover, the quantity and the quality of information, which strongly depend on size and resolution of the fingerprint images, have a significant impact. As mentioned before, the biometric performance is a tradeoff between security and convenience, which additionally affects the design of an algorithm.

[11] IoT - **I**nternet **o**f **T**hings

4.3 Research

4.3.1 Intention

In order to get an overview of common practice and to find appropriate algorithms for this project, a research is carried out. The following basic requirements for the selection of promising algorithms are applied:

I Pure correlation-based matching

II Partial fingerprints (restricted information)

III Restricted computational power

4.3.2 Outcomes

This algorithm research comprised over 35 papers and theses published between 1998 and 2019. Two periods with an increased number of publications can be observed in the early 2000s as well as between 2014 and 2018. The first period was around the fingerprint verification competitions. The second period was after the introduction of the first fingerprint sensors in smart phones.

None of the proposed approaches cover all of the requirements above. Most of the result evaluations focus primarily on the biometric performance. Requirement III in particular is barely considered. In this context, there is often no separation between enrollment and verification or identification. In addition, pure correlation algorithms are rare. Most of the approaches utilize the regions around minutiae. In summary, algorithms that fully meet the criteria for this project cannot be found.

The following points outline the common practice that can be observed:

- Most of the algorithms use standard fingerprint normalization and enhancement techniques to preprocess the images.
- The features are mostly square-shaped regions, called windows, composed of the gray-scale values. The edge length varies between 16 px and 50 px.
- Some algorithms select regions based on the amount of discriminatory information. Most of the algorithms use the regions around minutiae to guarantee that. With partial fingerprints, there is often no selection and all available information is used.

- Large displacements and rotations are compensated by a coarse alignment. This is mostly based on singular points or minutiae. A fine alignment is often done by shifting the feature pixelwise over a bigger search window for different rotations. The compensation of rotation is a bigger issue than displacement.
- A variety of approaches are used for the matching stage:
    - The correlation score is used as a validation stage for minutiae matching.
    - The peak or average values of the distance functions Euclidean distance, normalized cross correlation and correlation coefficient are used as matching score.
    - The relative matched positions of the window features are used as score.

In the electronic appendix an examination of the algorithms of helpful papers can be found. Those are compared concerning the following criteria:

- Algorithm parts:
    - Enhancement / pre-processing
    - Feature representation
    - Alignment – displacement / rotation
    - Matching score computation
- Reaction to / measures to:
    - Intra-class variations
    - Reduction in computational effort
    - Guarantee of enough discriminatory information

The papers compared are listed below:

- [Baz+00] A Correlation Based Fingerprint Verification System
- [Kov00] A Fingerprint Verification System Based on Triangular Matching and Dynamic Time Warping
- [RRJ02] Fingerprint Matching using Feature Space Correlation
- [NJ04] Local Correlation-based Fingerprint Matching
- [Lin+07] Correlation Based Fingerprint Matching with Orientation Field Alignment

- [Li+08] Fingerprint Matching Using Correlation and Thin-Plate Spline Deformation Model
- [WS11] Fingerprint recognition system for low quality images
- [ZBS14] Partial Fingerprint Identification Through Correlation-based Approach
- [SSB19] Fingerprint-Matching Algorithms

4.4 FVC databases

In order to establish a common benchmark for fingerprint recognition algorithms, the first fingerprint verification competition was organized in 2000. This benchmark should allow to compare the biometric performance and to track improvements in fingerprint recognition algorithms. As part of this competition, four databases were created using three different state-of-the-art sensors and an artificial generator. The so-called *FVC2000* was an international open competition where companies and academic institutions could participate. It was not meant as an official performance certification, it was conceived as a *technology evaluation*[12]. [Mai+02a]

Further competitions with further specially collected databases were in 2002, 2004 and 2006. A web-based evaluation system called *FVC-onGoing* was set up in 2009. For more information about the circumstances and the results of all of the competitions, please refer to [Bio20] and the links provided there.

The overview on the next page summarizes the features of the two FVC databases that are set by the hosting company as input of the system requirements analysis. In addition, an image of each database is shown in figure 4.3.

[12] Technology evaluation as defined in [MW02, p.7]: »*The goal of a technology evaluation is to compare competing algorithms from a single technology. Testing of all algorithms is carried out on a standardised database collected by a “universal” sensor.* [...]«

FVC2000, DB2, [Mai+02a]

- Capacitive sensor »TouchChip« by ST Microelectronics
- Resolution: 500 dpi
- Image size: 256 px × 364 px
- 110 fingers (100 finger in evaluation set A, 10 finger in training set B)
- 8 impressions per finger

FVC2002, DB3, [Mai+02b]

- Capacitive sensor »100SC« by Precise Biometrics
- Resolution: 500 dpi
- Image size: 300 px × 300 px
- 110 fingers (100 finger in evaluation set A, 10 finger in training set B)
- 8 impressions per finger

Information on the collection process of both databases can be found in appendix D.

Figure 4.3: a) FVC2000 DB2 image, based on [Mai+02a, DB2]
b) FVC2002 DB3 image, based on [Mai+02b, DB3]

5 Conception

Due to the lack of correlation-based algorithms that meet all the requirements defined for the research, the system requirements analysis is realized in a very fundamental way. The research revealed a high degree of variance in the disclosed approaches. Even if no approach as a whole can be adapted to this project, promising components need to be examined in order to understand the dependencies between biometric performance and computational effort. Moreover, the examination of different sensor sizes and resolutions require a pre-processing stage for the preparation of the fingerprint images.

In order to handle this variability, a decomposition of enrollment and verification process into modules is necessary. An environment is required that implements a fingerprint verification system in a modularly configurable manner.

The target hardware architecture cannot be used as platform for such an environment. Consequently, the computational effort on the embedded system must be measured separately. In order to establish a relation to the results of the analysis environment, the measured value must be scalable. This is described in detail in section 7.3.

In the process of the analysis, essential parameters of each module must first be identified and then examined independently. Investigating the impact of a parameter in terms of the biometric performance requires a biometric test for each parameter value. In the following, an estimate of the possible scope of such an investigation is made. The *feature size* is used as example parameter. The research revealed square-shaped window features with a minimum and maximum edge length as used below. A corresponding parameter sweep can be set up as follows:

- Parameter sweep *featureSize*
    - From 16 px to 50 px in steps of 2 px

This results in 18 biometric tests. A consideration of the three different image distance functions increases this count to 54.

For a single biometric test, the number of comparisons is at a maximum if the ratio of enrollment and verification images is one to one. With the 880 images of a FVC database, this results in

$$\begin{aligned} n_{Comparisons} &= n_{Images,enrollment} \cdot n_{Images,verification} \\ &= 440 \cdot 440 = 193{,}600 \end{aligned}$$

for the maximum number of comparisons[13]. Consequently, the total number of comparisons within the feature size investigation amounts to more than 10 million.

Due to that scope, the environment must be capable to handle a high amount of data and long test duration. With the estimated number of comparisons, duration can be expected in an hour-span and memory consumption possibly up to a GB-range.
Besides that, the result processing of a single biometric test is not possible before it is completed. All data of the test must be available for a result processing after test execution. The selection of applications used for development of the analysis environment is mainly affected by these circumstances.

With regard to the amount of data, an underlying database system is reasonable. The layer above must provide the interface to the database as well as a performant environment for computing. In addition, a user interface for the configuration of a biometric tests must be provided.

Figure 5.1 on the next page illustrates the functional interaction of the analysis environment in its simplest form. The fingerprint pattern symbolizes the FVC databases as input for the analysis. The charts symbolize the outcomes of a biometric test. The orange-black token symbolizes the user.

[13] Please note that this assumes a separated enrollment process for each of the four enrollment images per volunteer, which is not common. The calculated number of comparisons is a possible extent. The comparison scheme used in this project is explained in section 7.2.2.

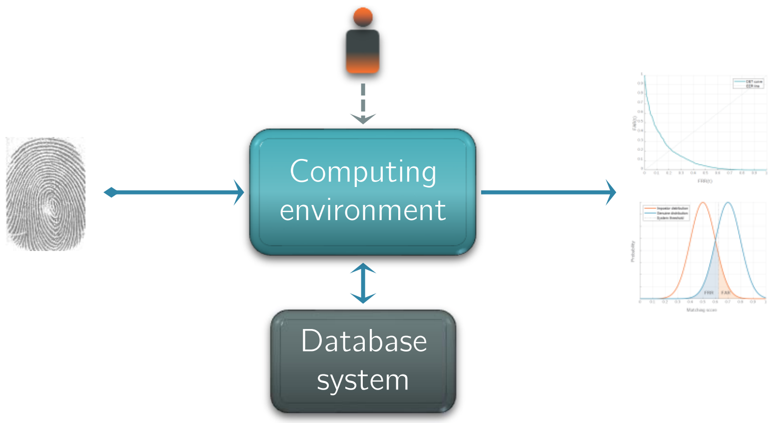

Figure 5.1: Analysis environment - functional interaction

The hosting company recommended the database system SQLite[14], which is used for biometric tests in similar applications in the department.
Due to its performance and the characteristic as a interpreter language, MATLAB® is selected as computing environment. It additionally provides a comprehensive set of image processing algorithms through the Image Processing Toolbox. Please be referred to [The21] for more information on this add-on.
Different SQLite interfaces are available for MATLAB®. The open source interface mksqlite in version 2.7 is used in this project. Please be referred to [Kor21] for more information on the interface.

The environment must be additionally feature a high extensibility. An implementation of further parameters should be a common measure in order to react to the dynamic analysis process. At the same time, a reproducible test handling and result evaluation must be assured to compare different setups.

Furthermore, in order to ensure a certain structure compatibility of the implementations of matching algorithms within the department of the hosting company, the following three basic functions should be implemented:

- *createEnrollmentTemplate*
- *createVerificationTemplate*[15]
- *matchTemplates*

[14] SQLite is a software library that provides a relational database management system, [SQL21]. The tutorial in the source can be recommended by the author.
[15] A so-called verification template is created from the captured fingerprint during the verification process. The term template is here not used only for the enrollment process.

At this point it is useful to clarify the procedure of the verification system of this project. Figure 5.2 illustrates this procedure. It shows the mentioned pre-processing stage for the input images as well as the algorithm implementation structure.

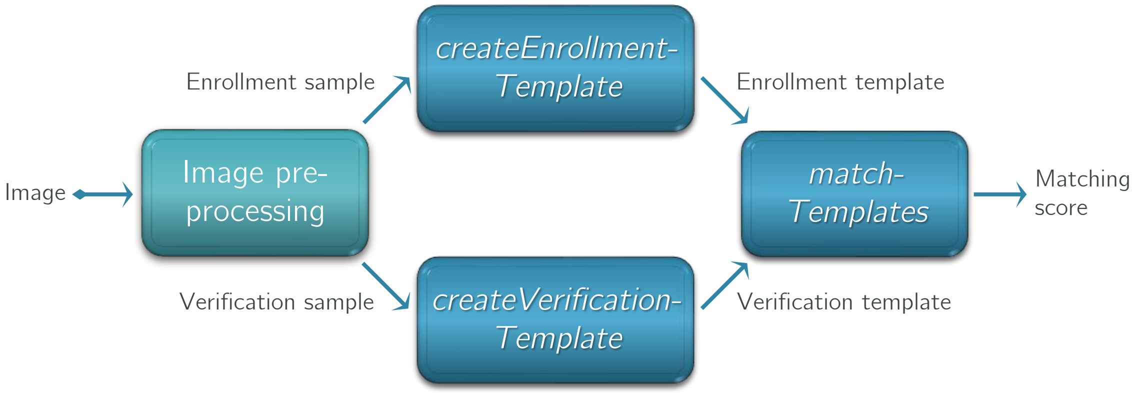

Figure 5.2: Verification system - procedure

The parts of the flow chart in figure 5.2 correspond to the following modules of enrollment and verification process as shown in figure 2.1:

- Image pre-processing
    - *Capture* of both processes
- *createEnrollmentTemplate*
    - *Feature extraction* and *template creation* of the enrollment process
- *createVerificationTemplate*
    - *Feature extraction* of the verification process
- *matchTemplates*
    - *Matching* of the verification process

The main information between two modules is transferred in a so-called *information container*. Its content is one or more gray-scale images.

The following terms are used to refer to the different types of these information containers in the verification system:

- *Image*
  - Raw image from a fingerprint database
- *Enrollment sample*
  - Pre-processed image for enrollment
- *Enrollment template*
  - Enrollment part of the comparison composed of enrollment sample(s)
- *Verification sample*
  - Pre-processed image for verification
- *Verification template*
  - Verification part of the comparison composed of one verification sample respectively its features

The verification system described above is implemented by the analysis environment.

The complete development, implementation and testing of the analysis environment is part of this project and described in the next chapter 6. The system requirements analysis is documented from chapter 7 on.

The environment is called *Correlation Analysis Environment* (CAE).

6 Correlation Analysis Environment (CAE)

This chapter describes the development of the environment that forms the foundation for the analysis of correlation-based matching algorithms. As mentioned in the conception, the system requirements analysis is a dynamic process. The CAE must feature a high extensibility in order to enable a simple implementation of further parameter during the analysis.

The following sections describe the development of the framework that makes this extensibility possible. This is referred to as CAE version 0.9. It provides the basic functionality and the prepared configurability, but with limited configuration options. The requirement analysis and the consequent architecture overview is described in section 6.1, followed by the fine architecture in 6.2 and the implementation in 6.3. The description of the extension process can be found in section 6.4. Section 6.5 describes the testing procedure applied.

The documentation of the CAE includes a set of external files. Please be referred to the electronic appendix, which is described in appendix A.

6.1 Requirement analysis and architecture overview

In the following, the requirements for the development of the analysis environment are described. An architecture is derived directly from these requirements and then refined in the next section.

6.1.1 MATLAB®-SQLite interface

As described in the conception, due to the number of comparisons and the expected amount of data, an underlying database system must be used. MATLAB® and SQLite are the applications selected for the development of the CAE.

The following terms are used throughout this chapter to describe the components of these applications.

- *Process*
  - A MATLAB script that includes one or more CAE modules as well as supporting functionality
- *Module*
  - A MATLAB section inside a process
- *Function*
  - A MATLAB function, called by a module
- *Database*
  - An SQLite database in the form of a .db file that contains one or more SQLite tables
- *Table*
  - An SQLite table that contains one or more columns

The use of the interface between the applications is structured in two levels. Figure 6.1 shows these levels with the corresponding components.

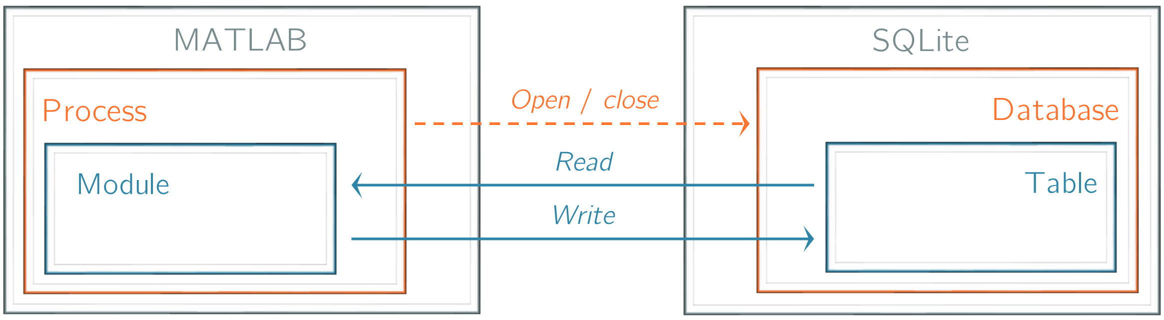

Figure 6.1: Structure of the MATLAB®-SQLite interface

At the so-called *process level*, the connection to a database is managed. This is referred to as *open* or *close*. At the so-called *module level*, data in form of a number of rows of a table are transferred. This is referred to as *read* or *write*. The arrow directions of the commands *read* and *write* in the figure above illustrate the data flow.

A function does not use the interface. All necessary information is provided by the module with the function call.

6.1.2 System overview

The FVC databases are the input of the analysis. In addition to the images, the hosting company provides SQLite databases that consist of basic information on the fingerprint images for each FVC database. This includes the path to the image file, identification numbers for each image and each volunteer as well as further information. The images must be imported into the CAE and labeled using the information in the provided SQLite database. The output of the CAE must be the characteristic charts for performance evaluation as well as further information of the carried out biometric tests like the computational effort.

With regard to the scope of the analysis, some specific requirements for the user interface are appropriate. Corrupted result as a consequence of bugs or wrong user input are highly critical, especially because they might not directly visible during result evaluation. Thus, the complete procedure must be logical and transparent to the user. Even if the analysis of single comparisons are out of the scope of this project, for testing and debugging purposes the access to the insight of the modules must be possible. Furthermore, wrong user input must be avoided. Subsequently, with respect to a continuation of the project, the CAE must be programmed and documented in a comprehensible way.

Figure 6.2 shows the CAE as a black box. The user interface as well as input and output are illustrated with the symbols that have already been used in previous figures. The little database symbol inside the fingerprint illustrates the SQLite database that is provided to each FVC database.

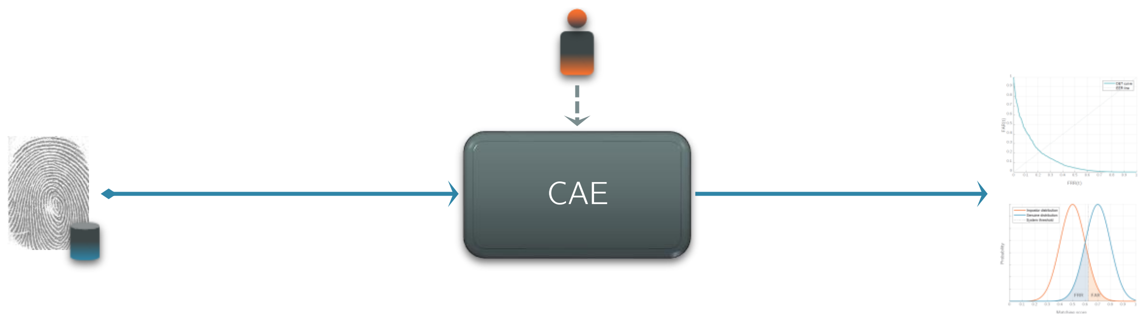

Figure 6.2: System overview - CAE as a black box

The CAE procedure may include several biometric tests. A series of biometric tests that are carried out simultaneously in the environment is referred to as a *CAE test* throughout the thesis. The parametrization of a biometric test is called a *test configuration*.

6.1.3 Process level

A CAE test involves a complex procedure from configuring a series of biometric tests up to comparing the results of those tests. An implementation of this procedure in one single process would be limiting and inflexible. In the event of an error, the entire procedure would have to be repeated. In general, a division of a CAE test into different processes contributes to its reproducibility and to the extensibility of the environment. Furthermore, this supports a modular overall structure and thus facilitates programming and testing. The connection between the processes must be handled by a defined format of input and output databases.

The requirements above make the following division reasonable:

- CAE test
    - I *Creation process* that comprises the setting of one or a series of test configurations
    - II *Execution process* that comprises a biometric test per test configuration
    - III *Evaluation process* that comprises the result evaluation of each test configuration and its visualization

Figure 6.3 illustrates the CAE on process level. Within the creation process, the input databases must be imported. Between the processes, data is stored in two different databases. User interaction is required to start each process.

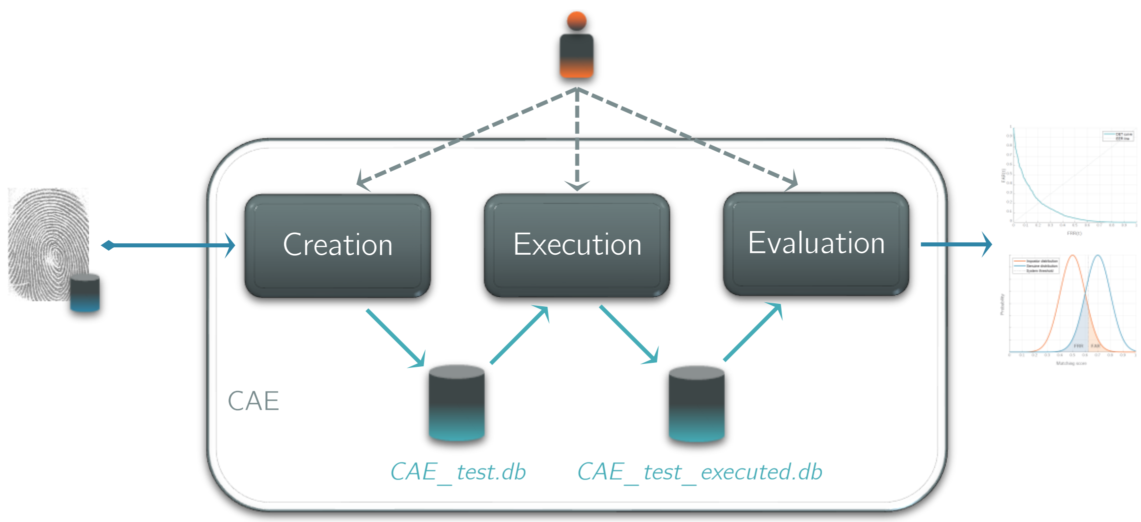

Figure 6.3: CAE - Process level view

6.1.4 Database interaction

The CAE must be structured in configurable modules of a fingerprint verification system. This is explained in the next section 6.2. First, the interaction of these modules with the database system is explained.

Figure 6.4 illustrates two modules within a process. The arrow on the bottom of the figure indicates the temporal sequence. The arrows from and to the database relate to the command types introduced in figure 6.1. During a process, an active database connection is established between the *open* and *close* commands. At module level, it is possible to work with the data from the opened database using the commands *read* and *write*.

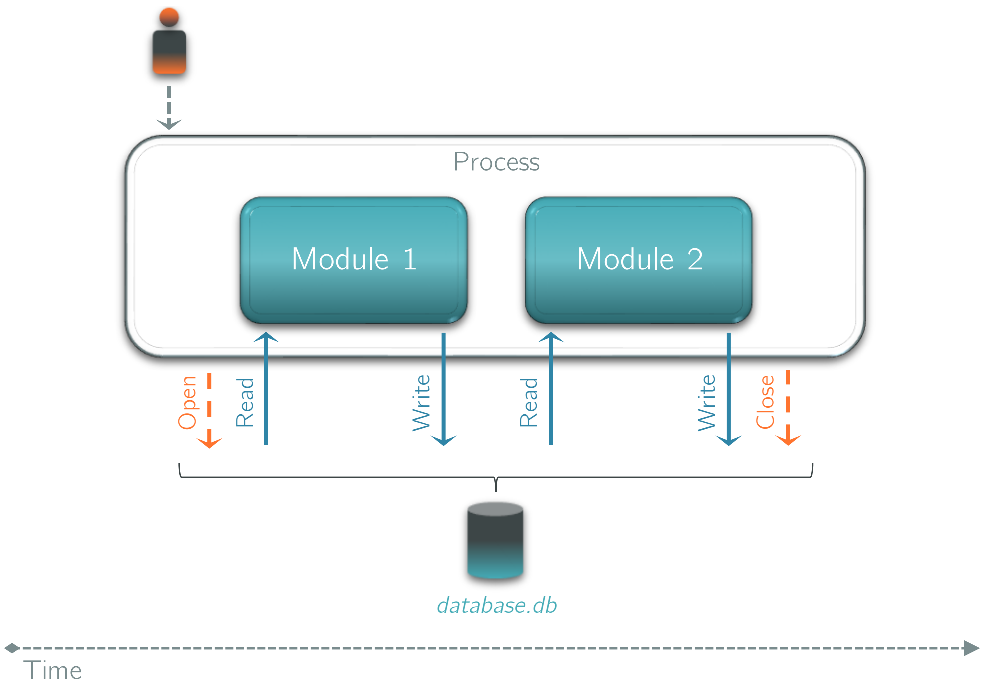

Figure 6.4: CAE - Database interaction

Each process opens a database at the beginning, works with it and closes it at the end. In order to realize this in compliance with the procedure in figure 6.3, the input database of the execution process must be copied and renamed. Thus, the output database of the creation process remains unchanged. This ensures the reproducibility of a CAE test.

6.2 Detailed architecture

This section describes the deeper levels of the architecture and the implementation of the verification system.

6.2.1 Module level

A module is located within a process. Figure 6.5 illustrates the basic functionality of this level. The interaction with the database takes place via tables.

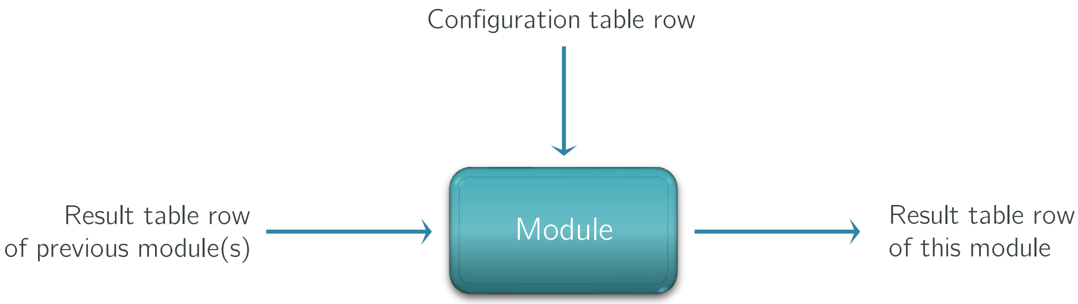

Figure 6.5: CAE - Module level

There are two main types of tables in the CAE. A *result table* represents the input respectively the output of an module. This includes necessary information to relate the data of the different tables as well as the corresponding information containers. A *configuration table* includes the parametrization to the instructions that are applied to a information container inside the module.

Thus, the functionality of an module can be described by an entirety of configurations that are applied to an entirety of one information container type and saved as an entirety of another information container type.

6.2.2 Function level

A function is located within a module. Figure 6.6 illustrates its basic integration.

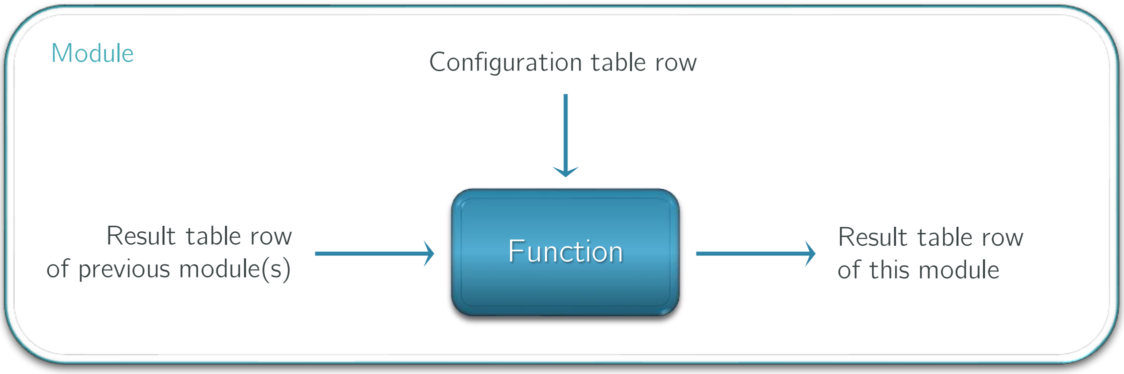

Figure 6.6: CAE - Function level

A function implements the application of one configuration to one information container. As a result, one new information container is stored in the result table of the module.

There is no interaction with the database on this level. A function is called inside a loop of a MATLAB® section, which represents the module.

6.2.3 Verification system

The section describes the structure of the verification system, that is implemented in the test execution process.

The structure of the verification system is based on the considerations in the conception. Figure 6.7 on the next page shows the module structure derived from figure 5.2. The figure below illustrates this in terms of a CAE test. The dashed lines illustrate the flow. They are not meant as input or output of the modules because a database interaction as shown in figure 6.4 is applied to every module.

The individual modules are briefly outlined below the figure on the next page.

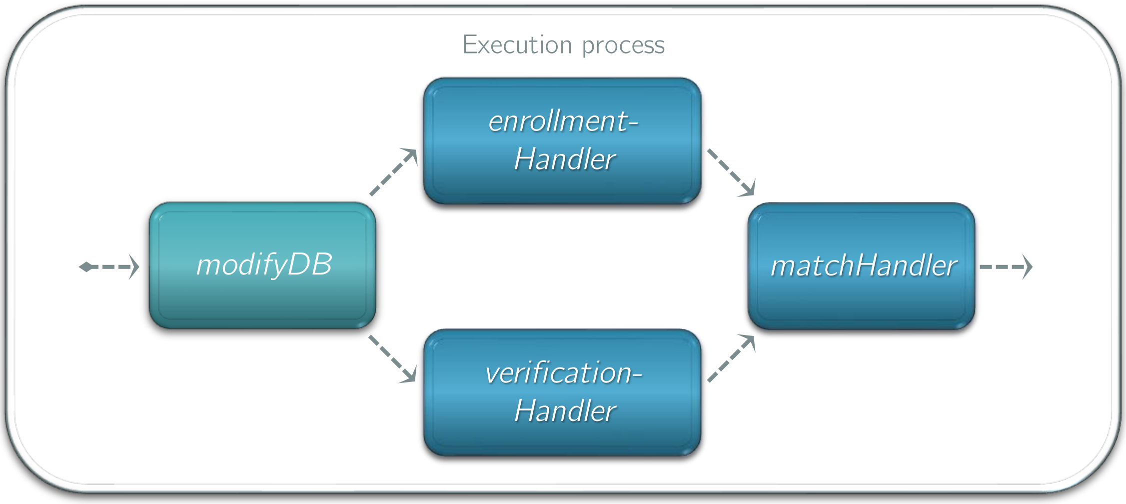

Figure 6.7: CAE - Module structure of the verification system

- *modifyDB*
  - This module describes the pre-processing of all images of the input FVC database. The output is the entirety of the enrollment and verification samples for all applied CAE test configurations.
- *enrollmentHandler*
  - This module describes the processing of all enrollment samples. The output is the entirety of the enrollment templates for all applied CAE test configurations.
- *verificationHandler*
  - This module describes the processing of all verification samples. The output is the entirety of the verification templates for all applied CAE test configurations.
- *matchHandler*
  - This module describes the matching of all combinations of enrollment and verification templates that fulfill the matching configurations. The output is the entirety of the scores and further results for all applied CAE test configurations.

6.3 Implementation

This section describes the CAE hierarchy of MATLAB® scripts and functions as well as the implementation of the distance measures. Please be referred to the commented source code of the corresponding files in the electronic appendix for the detailed implementation.

6.3.1 Hierarchy of scripts and functions

The names of the source files, which implement the architecture hierarchy of processes, modules and functions, are listed below:

- Script *createTest.m* (creation process)
  - Function *createConfigurationStruct.m*
- Script *executeTest.m* (execution process)
  - Function *createSample.m* (module *modifyDB*)
  - Function *createEnrollmentTemplate.m* (module *enrollmentHandler*)
  - Function *createVerificationTemplate.m* (module *verificationHandler*)
  - Function *matchTemplates.m* (module *matchHandler*)
- Script *processResults.m* (evaluation process)

The SQLite commands *open* and *close* on the process level are realized by direct commands to the interface. The table creation as well as the commands *read* and *write* are wrapped in MATLAB® functions, which implement the desired functionality by several commands to the interface. The names of the function are listed below:

- SQLite integration
  - Function *sqlite_create.m*
  - Function *sqlite_set.m*
  - Function *sqlite_get.m*
  - Function *sqlite_getRowCount.m*

6.3.2 Image distance functions

The distance measures, described in section 4.1, are implemented in a manner that enables an easy porting to the target hardware architecture. They are listed below with their underlying equations and their short names within this project:

- Sum of squared differences, based on equation (4.2)
  - Short name - *SSD globalN*
- Euclidean distance, based on equation (4.1)
  - Short name - *euclid globalN*
- Normalized cross correlation, based on equation (4.6)
  - Short name - *normCC*
- Correlation coefficient, based on equation (4.9)
  - Short name - *corrCoeff*

The implementation of the correlation coefficient is based on the implementation in [BB16, p.571].

The CAE implementation of a distance measure are referred to as an *image distance function* in the following chapters.

6.3.3 Information on applications and interfaces

The CAE is programmed and used with MATLAB® R2020a Update 5 (9.8.0.1451342) featuring the add-ons Parallel Computing Toolbox version 7.2 and Image Processing Toolbox version 11.1.

The SQLite interface mksqlite is used in version 2.7.

6.4 Extension

The CAE can be expanded by adding a new parameter, which means a new column, to a configuration or a result table. The implementation of the functionality of this new parameter is limited to the corresponding function.

For example, a parameter that affects only the creation of a verification template is implemented in the function *createVerificationTemplate*. This isolation of the parameter implementation is possible for the following reasons.

- The overall procedure of the processes is independent of the parameters.
- The SQLite interface on the module level works with tables respectively single rows of the tables. Therefore, a new column does not affect the module implementation.
- Due to the independence of the modules to each other, other modules do not have to be taken into account. The change of the information container by the parameter is stored implicitly in its pixel values.

However, in addition to the implementation on the function level, the CAE have to be changed on definite locations. The following procedure outlines the required steps for adding of a new configuration parameter to the CAE:

- Define the new parameter for database creation (function *sqlite_create.m*)
- Make the parameter configurable
  (user input area in process *createTest.m* / function *createConfigurationStruct.m*)
- Implement the parameter in the corresponding function
- Testing procedure (please be referred to the following section)

Due to the architecture, a new configuration parameter can simply be added without changing the implementation outside a function.

During this project, four CAE versions are used throughout the process of the system requirements analysis.

6.5 Testing

The proper functionality of the environment must be ensured after every change outside of the user input areas. The validity of the results must be guaranteed during the entire analysis process. Consequently, a comprehensive testing is required with each new version.

The test procedure can be described with a bottom-up approach. The functions are tested first, followed by the module level and the process level. At the end of the procedure the environment in its entirely is tested.

The release of the version 1.00 includes a complete test of all parts of the environment. For further versions, the comparability of CAE tests of different versions is utilized in order to reduce the extent of the test procedure. A configuration from a previous version can be realized with the current version by setting all added configuration parameters to their identity value. Thus, the correctness of the overall procedure can be confirmed by the equality of the results of these tests.

Consequently, as of version 1.01, the test procedure is divided into two main parts. First, every component that has been changed from the previous version is tested. Second, the overall functionality is tested by comparing the results of a CAE test with those of the previous version.

The specific tests for all versions are documented in an external Excel file. The script *testBench.m*, which contains the tests of the parameter functionality, is also included in the electronic appendix.

7 Structure of the system requirements analysis

The system requirements analysis involves the implementation of parameters of correlation-based matching in the CAE and the investigation of their impact on biometric performance and computational effort. This chapter describes preliminary considerations as well as the documentation structure of the analysis in the thesis.

The methodology of the analysis is explained in the following section 7.1. The preparation of the FVC databases is described in section 7.2. The measurement of the computational effort on the target hardware architecture is described in section 7.3.

The documentation of the analysis can be found in chapter 8 and 9. This division corresponds to the two phases of the analysis process, which are explained in the following.

7.1 Methodology

7.1.1 Analysis process

The algorithm research reveals so-called windows as features of correlation-based matching. A score is calculated for each window. These scores are combined into one matching score of the comparison. This characteristic of correlation-based matching enables a qualitative analysis of single features.

Due to this possibility, the analysis process can be divided into two *phases*:

- Phase 1 – Analysis of verification templates composed of one feature
  - Short name: Phase 1 - Distinction
- Phase 2 – Analysis of verification templates composed of several features
  - Short name: Phase 2 - Algorithm

This simplification contributes to a clear structure of the analysis process. In the first phase, the distinction based on one feature is examined. Afterwards in the second phase, the impact of using several features is examined. A direct analysis of the case in the second phase is expected to lead to unclear results because the property of a single feature represents an additional variability. In addition, the insights of the first phase can be assumed as given in the second phase. That reduces the number of variations and increases the scope of the analysis.

Both phases are each divided into three different *parts*. The first part comprises the creation of reference outcomes and the optimization of the CAE test duration. Subsequently, an independent investigation of the parameters of correlation-based matching can take place. A further division of that into a second and a third part is done because of the trade-off between biometric performance and computational effort. Hence, the second part of each phase includes the parameters that are expected to improve the biometric performance. The third part includes the parameters that are expected to reduce the computational effort.

In summary, the system requirements analysis is carried out as follows:

- Phase 1 - Distinction
    - Part 1 – Positioning
    - Part 2 – Optimization of the biometric performance
    - Part 3 – Reduction of the computational effort
- Phase 2 - Algorithm
    - Part 1 – Positioning
    - Part 2 – Optimization of the biometric performance
    - Part 3 – Reduction of the computational effort

This structure plus a phase introduction and a phase conclusion outline the chapters 8 and 9. The conclusion includes the summary of the phase and a comparison of the reference outcomes with the outcomes of a final configuration.

Each part of a phase involves several *investigations*. In this project, the term investigation refers to the analysis of one parameter such as *feature size* or *rotation*.
The analysis process is characterized by a step-by-step procedure. Consequently, a new investigation is not started until the previous one is finished. Under certain circumstances, the outcomes of an investigation can affect the configurations of the following ones.

An investigation includes one or more *CAE tests*, which comprise one or more *configurations*. For each configuration, a biometric test, which is defined by the set of *configuration parameters*, is carried out.

Figure 7.1 illustrates the described structure using the example of the investigation of the feature size.

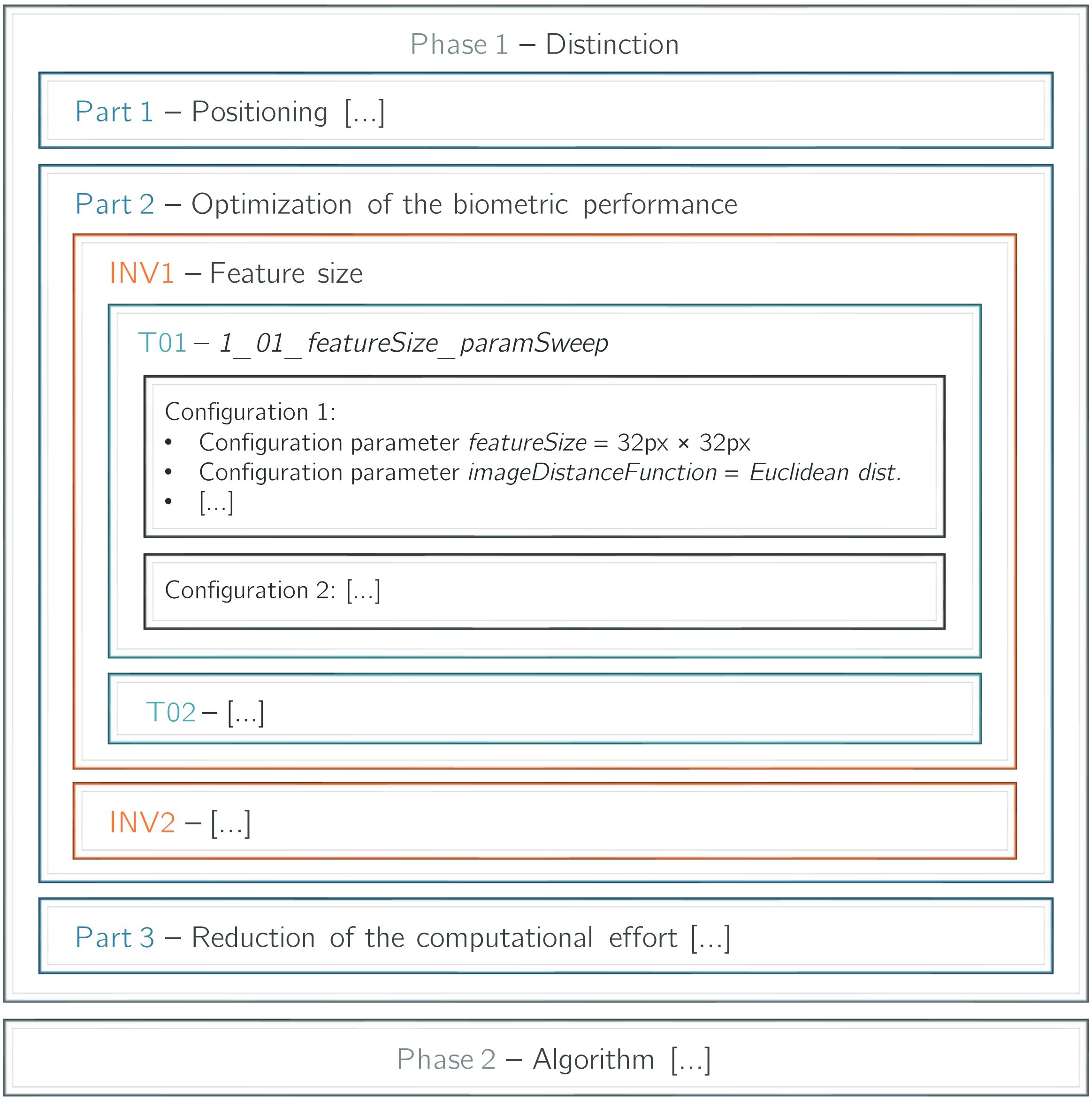

Figure 7.1: Analysis structure in this project,
»[...]« implies structure levels that are not shown for reasons of clarity,
INV: investigation, T: CAE test

The following formatting applies to the thesis and the electronic appendix:

- The investigation with number 1 is abbreviated by INV1. The numbering takes place consecutively for the entire project.
- The CAE test with number 1 is abbreviated by T01. The numbering takes place consecutively for the entire project.
    - The name of a CAE test follows the structure » *phaseNr_testNr_investigationIdentifier_testIdentifier* «, for example » *1_T01_featureSize_paramSweep* «.

The documentation of the analysis in the thesis includes all investigations and the structure levels above them. Configurations and outcomes of the CAE tests are documented in an external PowerPoint file. In addition, the *outcome database* of this project is provided as electronic appendix in form of an SQLite database file.

As mentioned in the conception in chapter 5, a single comparison is only analyzed in corner cases and for testing the CAE. The results of that are therefore not explicitly documented.

7.1.2 Documentation structure of an investigation in the thesis

At the beginning of an investigation subsection, an outline is provided. This includes an overview of the CAE tests as well as information about the parameter investigated. Subsequently, the relevant outcomes, separated concerning biometric performance and computational effort, are documented. Finally, the insights gained and their influence on the further analysis are described.

In summary, every investigation subsection is structured with the following headlines:

- Outline
- Biometric performance
- Computational effort
- Insights gained

The names of the CAE tests in the outlines can be used for an orientation within the documentation in the electronic appendix.

The parameter under investigation is referred to as *parameter* throughout the following chapters. A CAE test configuration is referred to as *configuration*.

The outcomes of the CAE tests are mainly documented using tables. The values in the tables are partly colored to indicate a good / best performance or a bad / worst performance within the table.

7.2 Preparation of the FVC databases

The following section describes the actions required to enable the usage of the FVC databases.

7.2.1 Problem formulation

An analysis of different sensor sizes requires cropping the fingerprint images. This leads to comparisons of partial fingerprints, which does not conform to the original use case of the databases. The original use case of the FVC2000 DB2 can be derived from the following two bullet points, which are quoted verbatim from [Mai+02a]. The complete description of the database collection process can be found in appendix D.

- »*The presence of the fingerprint cores and deltas is not guaranteed since no attention was paid on checking the correct finger position on the sensor.*«
- »*The acquired fingerprints were manually analyzed to assure that the maximum rotation is approximately in the range [-15°,+15°] and that each pair of impressions of the same finger has a nonnull overlapping area.*«

An utilization of the databases as planned in this project was not intended during the collection process. An overlapping area cannot be guaranteed with partial fingerprints.

In order to focus the analysis on correlation-based matching, errors of the capturing stage need to be excluded from the start. The verification system of this project works with already collected databases. Thus, capture errors comprise unsegmented images and genuine image pairs with insufficient overlap. To avoid this, two initial actions are required that form the foundation of the sample creation:

- The definition of a cropping center for each image
- The definition of the maximum size of a cropped image

The center of the image cannot be used for the first definition because some fingerprints are only captured in a part of the image. Additionally, it is not assured that the same part of the finger is captured for all images from the same volunteer. Consequently, a static cropping center does not fulfill the requirements.

The hosting company provides an SQLite database that consists of basic information on the fingerprint images for each FVC database. This includes a COG[16] that represents the center of the captured fingerprint within the image. The coordinates of those points can therefore be used as the foundation for the first definition above.

The maximum size of a cropped image is given by the maximum sensor size to analyze. The mentioned capture errors are avoided even with smaller cropped images as long as they relate to the same cropping center.

Assuming segmented samples, the compliance of the following condition would prevent all capture errors:

- For genuine comparisons, the verification template has a complete overlap with the enrollment template.

Using the FVC databases with the pre-calculated COGs, this is realizable if the enrollment template contains a larger area of the fingerprint than the verification template. This conforms to the use case of matching algorithms that deal with partial fingerprints, but it requires a visual inspection of every possible genuine comparison to assure the above condition. If the condition is not satisfied, changing the COG of the problematic images is the method to react.

In order to simplify this inspection, the number of possible combinations need to be limited by defining the size of enrollment and verification template. This has to be done separately for both analysis phases. Furthermore, with regard to the effort and the accuracy of a visual inspection, the above condition need to be changed:

- For genuine comparisons, the verification template has as much as possible overlap with the enrollment template.

As long as each cropping operation relates to the definitions of cropping center and maximum size, this condition is sufficient for the analysis in this project. The definitions hold throughout the analysis process and therefore do not influence the independence of a parameter investigation.

[16] COG - **C**enter **O**f **G**ravity – Centroid of the image based on the pixel gray-scale values

7.2.2 Definition of the comparison scheme

The analysis and the visual inspection require a definition of the extent of a biometric test. It includes the number of enrollment and verification images per volunteer and the maximum size of a sample. This is called the *comparison scheme* of the phase.

Number of enrollment and verification images per volunteer

In order to achieve a certain independence of the comparisons while maintaining a certain test size, a biometric test have to feature the following conditions:

- Every fingerprint image is either part of an enrollment or a verification template.
- Every volunteer is represented by one enrollment template.

Due to the size of the databases and their utilization, three out of eight images are used for enrollment. This results in the following number of comparisons per biometric test:

- Total comparisons: 60,500
    - Genuine comparisons: 550
    - Impostor comparisons: 59,950

The number of genuine comparisons is the critical one in terms of a sufficient test size. The application of the »Rule of 30« is a measure for predicting the error rates of a biometric system when applied to the entire population. This is only necessary to assess the error rates of the *final configuration* of the second phase.
The impact of a parameter is investigated by evaluating the development of the error rates for various parameter values. Consequently, the independence of the comparisons can be reduced in favor of the test size. The number of the genuine comparisons can be increased by disregarding the second condition above. Therefore, for the first phase, each of four of the eight images are used for an individual enrollment.

Maximum size of a sample

The following selection of the sizes follows the previous considerations. In order to guarantee a sufficient overlap, the enrollment template must be larger than the verification template.

For partial fingerprints, an enrollment template usually consists of several samples. During the enrollment process, the individual usually presents their finger several times in order to capture different parts of the fingerprint. Some algorithms check the overlap of the captured samples in order to guarantee as much fingerprint area as possible.

Due to the small number of enrollment images per volunteer, this is not possible with the FCV databases. Moreover, the composition of an enrollment template describes a sophisticated challenge, which is only indirectly addressed by the analysis of correlation-based matching. Hence, a division of the enrollment images into sensor-sized enrollment samples is not carried out. The size of an enrollment sample corresponds to the size of an entire image in this project. This applies to both phases.

The maximum size of a verification template corresponds to the different scenarios of the analysis phases. It describes the boundaries for which the visual inspection ensures a minimum of capture errors.
For the second phase, this size is defined by the maximum sensor size. With a resolution of 500 dpi, 144 px $\times$ 144 px corresponds to an area of 53.51 mm^2. That is slightly larger than the largest sensor size to analyze.
For the first phase, this size is defined by the maximum feature size. A feature size of 72 px $\times$ 72 px is selected. That size fits four times into the above size of the second phase. Furthermore, it is larger than the common feature sizes found in the algorithm research.

Figure 7.2 shows an image of the FVC2000 database with the applied verification sample sizes. The blue rectangle corresponds to a *phase-2-sample*. The cyan one corresponds to a *phase-1-sample*. The orange circle indicates the COG of the image.

Figure 7.2: Maximum sizes of a verification sample, based on [Mai+02a, DB2]

Comparison scheme

In the following, the comparison schemes are summarized:

- Phase 1 - Distinction
    - Enrollment images per volunteer: 4/8
    - Size of an enrollment sample: Corresponds to the enrollment image
    - Enrollment templates per volunteer: 4

    - Verification images per volunteer: 4/8
    - Maximum size of a verification sample (feature): 72 px × 72 px
    - Verification templates per volunteer: 4

    - Comparisons per biometric test: 193,600 (incl. 1,760 genuine ones)

- Phase 2 - Algorithm
    - Enrollment images per volunteer: 3/8
    - Size of an enrollment sample: Corresponds to the enrollment image
    - Enrollment templates per volunteer: 1

    - Verification images per volunteer: 5/8
    - Maximum size of a verification sample: 144 px × 144 px
    - Verification templates per volunteer: 5

    - Comparisons per biometric test: 60,500 (incl. 550 genuine ones)

These schemes are the foundation of the biometric tests in the analysis phases and thus also in the visual inspection.

A realistic use case of a matching algorithm is represented by the second phase. The »Rule of 30« is applied in the conclusion of the second phase in order to assess the accuracy of the final biometric performance of this project.

A comparison of images from different databases is not usual because of different sensors. Due to the exaggerated displacement of the FVC2002 DB3, which complicates an utilization for partial fingerprints, this database is used for control tests to avoid overfitting. The visual inspection is carried out for FVC2000 DB2.

7.2.3 Visual inspection

The following instructions outline the visual inspection of the image set of a volunteer. The term *inner rectangle* refers to a phase-1-sample of maximum size whereas the term *outer rectangle* refers to a phase-2-sample of maximum size.

I The outer rectangle of each image must contain only fingerprint pattern and no background.

- If not, change the COG.

II All inner rectangles must be findable in every other entire image.

- If not, change the COG of the affected images or set the restriction »onlyVerification« to the image(s) with small overlap to all other images. The condition above must be remain satisfied.

III All outer rectangles must be findable in every other entire image.

- If not, change the COG of the affected images or set the restriction »onlyEnrollment« to the image with the largest overlap to all other images. Disregard fingerprint quality in the choice of the image. The conditions above must be remain satisfied.

The inspection is carried out volunteer by volunteer.

7.2.4 Creation of the image role patterns

The COGs are changed directly in the SQLite database of the corresponding FVC database. The restrictions are added as new columns in the same tables. Using this information, nine different image role patterns are created for each phase. The roles of images without restrictions are set randomly in compliance with the comparison scheme.

These patterns are saved as MAT-files[17] and can be selected as presets during test creation.

[17]MAT-files are binary MATLAB® files that store workspace variables.

7.2.5 Avoidance of overfitting

In order to avoid overfitting, so-called *control tests* are carried out. This type of CAE tests provides input variation for identical test configurations. This supports the evaluation process by confirming or refuting a tendency of the main test. The input variation is realized through the image role patterns described above as well as through the second fingerprint database. Extent and moment of these tests are adapted to the current investigation.

The control tests are only documented in the external *outcome database*. Within the thesis and the PowerPoint files, only their comparison with the main tests is of interest. The control tests are indicated by the following abbreviations and text color:

- Control test with different image role pattern - CT P
- Control test with different image database - CT DB

7.3 Measurement on the target hardware architecture

The target hardware architecture for the verification system is *ARM Cortex M4* with the following configuration:

- Clock rate: 96 MHz
- Available memory: 32 kB
- Programming language: C

In the course of the system requirements analysis, the computational effort for various configurations has to be evaluated. The duration of a verification process and the maximum memory consumption are of interest.

Duration of a verification process

A verification process is composed of capturing the verification sample, creating the verification template and matching it with the enrollment template. Due to the use of the FVC databases, the capturing is not applicable to this project. Furthermore, the duration of the template creation is negligible compared to the duration of matching. The time needed for matching is referred to as the *duration of a comparison* in the following.

The duration of a comparison is affected by the properties of the templates and by the matching conditions. An implementation of the various configurations on the MCU[18] is not reasonable. A measurement of this duration within the CAE does not provide the circumstances of the hardware achitecture as well as the characteristics of the programming language. Furthermore, the measured value would not represent a realistic timing due to multithreading and pipelining of the operating system.

Hence, the duration has to be calculated using the results of both systems. This can be realized by breaking down the matching operation into a scalable unit. The duration of this smallest unit is measured on the MCU. The count of these are measured by the CAE for every configuration applied. A scalable unit of correlation-based matching that can be applied to all image distance functions is a correlation operation (C-OP).

As shown below, the duration of a comparison can be calculated by multiplying the C-OP duration, measured on the MCU, with the C-OP count, measured with the CAE.

$$t_{Comparison} = t_{C\text{-}OP} \cdot n_{C\text{-}OP} \quad . \tag{7.1}$$

The properties of a correlation operation are examined in the following. Figure 7.3 shows the definition of template matching in terms of fingerprints.

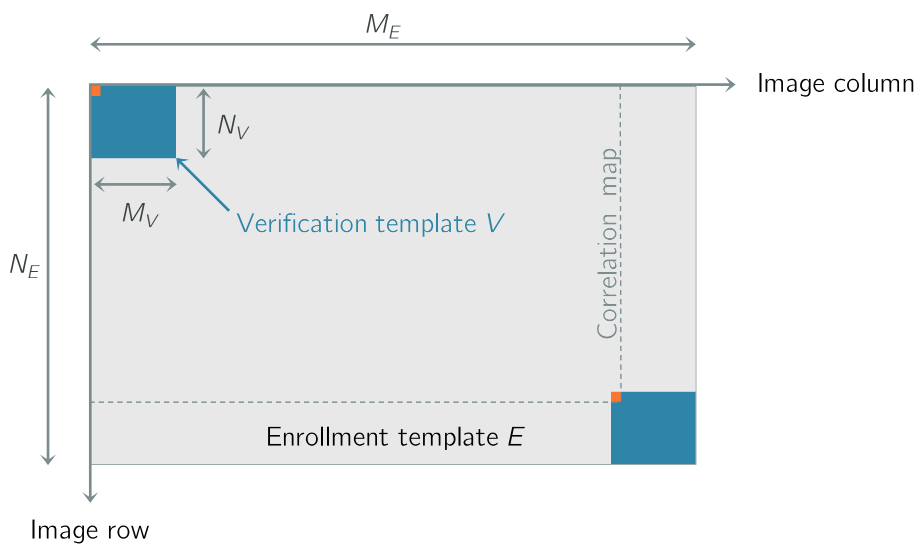

Figure 7.3: Definition - fingerprint template matching, based on figure 4.1

[18] MCU - **M**icro**c**ontroller **U**nit

In the figure above, the matching operation is illustrated without considering rotation. The correlation map contains a matching score for every offset. The orange pixels indicate the first and last offset.

The size of the correlation map, which corresponds to the number of correlation operations, is calculated by

$$n_{C\text{-}OP} = (M_E - M_V + 1) \cdot (N_E - N_V + 1) \ . \tag{7.2}$$

The CAE counts the correlation operations of every comparison and stores it as a result parameter. An association of this number to various configurations is realized by the test evaluation. The average number of the correlation operations of all comparisons per configuration is stored in the outcome database.

The duration of a single correlation operation is affected by the size of the verification template and the image distance function. Consequently, a measurement on the MCU is necessary for every combination of both.

However, a direct measurement of the duration of a single correlation operation is not reasonable. The image distance functions include computations that are required once per comparison. Thus, one comparison with a sufficient amount of correlation operations is implemented on the MCU for each image distance function. The size of the verification template is implemented as configurable. The correct porting is checked with the equality of the matching scores with the CAE implementation.

The number of cycles needed is measured using the integrated cycle counter in the *MCUxpresso* IDE. This cycle count is converted into a time by

$$t_{C\text{-}OP} = \frac{n_{Cycles}}{n_{C\text{-}OP,MCU} \cdot f} \tag{7.3}$$

where $n_{C\text{-}OP,MCU}$ is the number of correlation operations of the MCU implementation and f is the desired clock rate.

The cycles and the timings are documented in an external excel file. The measurement on the MCU is carried out using a clock rate of 12 MHz. The cycles are scaled to a clock rate of 96 MHz using the equation above.

The duration of a comparison describes an approximation of the duration of a verification process. The real duration is expected to be higher than the approximation. The exact relation depends on the effort made for the creation of the verification template.

The MCU implementations of the image distance functions are attached as electronic appendix.

Memory consumption

The memory consumption is maximum during matching. The templates, which are stored as an array of pixel intensity values, are much larger than the memory overhead needed for the correlation operation.

The correlation map is not stored in the MCU implementation. Any score lower than the current highest score is discarded.

Consequently, the sizes of enrollment and verification template are a sufficient approximation of the memory required.

8 Analysis phase 1 - Distinction

8.1 Introduction

The first phase comprises the analysis of verification templates that are composed of one feature. Figure 8.1 illustrates the comparison scheme of this phase as described in section 7.2.2. An enrollment template consists of one sample, which is an entire image. A verification template consists of one feature, which is cropped from the verification sample.

Figure 8.1: Comparison scheme of phase 1, fingerprint images are based on [Mai+02a, DB2]

The visual inspection guarantees a minimum of capture errors up to a cropping size of 72 px × 72 px. A size of 32 px × 32 px is used until the parameter *feature size* is investigated. This size is the most commonly chosen size in the approaches found during research.

The main tests are carried out with FVC2000 DB2. The control tests are carried out with FVC2002 DB3 (CT DB) as well as with FVC2000 DB2 using a different image role pattern (CT P). The databases are referred to as DB2 and DB3 in the following.

The biometric performance is evaluated based on the EER. The DET and the distribution chart of every main test can be found in an external PowerPoint file.

In this phase, the computational effort is evaluated based on the number of correlation operations per comparison. This is done by comparing its increase or decrease in relation to the reference configuration within the investigation. The relation is described by a so-called *C-OP factor*. An evaluation of the duration per comparison and the memory consumption is done in the second phase.

8.2 Part 1 - Positioning

8.2.1 INV1 - Reference outcomes

Outline

The aim of the first investigation is the creation of reference outcomes with the two FVC databases. This includes the following CAE tests:

- *1_T01_initialTest_DB2*
- *1_T02_initialTest_DB3*

A biometric test is carried out for each implemented image distance function.

Biometric performance

Table 8.1 shows the biometric performance of the initial configurations.

Table 8.1: INV1 - Biometric performance - references of the first phase

Image distance function	EER	
	DB2	DB3
SSD globalN	30.3%	39.8%
euclid globalN	30.3%	39.4%
normCC	40.4%	42.8%
corrCoeff	22.2%	31.1%

The following observations can be made:

- The correlation coefficient (*corrCoeff*) provides the best EER.
- The normalized cross correlation (*normCC*) provides the worst EER.
- The sum of squared differences (*SSD*) and the Euclidean distance (*euclid*) provide a similar EER, which is in between of the EER of the two other distance functions.

- The biometric performance with DB3 is worse overall, but not equally bad for all image distance functions. The differences are shown in table 8.2.

Table 8.2: INV1 - EER difference between DB2 and DB3

Image distance function	EER difference *EER DB2 – EER DB3* from table 8.1
SSD globalN	-9.5%
euclid globalN	-9.1%
normCC	-2.4%
corrCoeff	-8.9%

Furthermore, each image distance function shows its own characteristic in the shape and position of the impostor and genuine distributions. However, during the development of the CAE, the difficulty in visually assessing the DET and distribution chart were revealed, especially when it comes to small differences. Consequently, these charts are not part of an investigation documentation. Nevertheless, the charts of this investigation are shown in appendix B in order to visualize the performance development of this phase.

Computational effort

Table 8.3 shows the number of correlation operations (C-OPs) with the two databases.

Table 8.3: INV1 - Computational effort - references of the first phase

Input database	Enrollment template size	Verification template size	C-OPs
DB2	256px × 364px	32px × 32px	74,925
DB3	300px × 300px	32px × 32px	72,361

The following observations can be made:

- The effort with DB3 is slightly less than with DB2. This is due to the higher size of the DB2 images, which is equivalent to the size of an enrollment template.

Insights gained

Each image distance function provides an amount of distinction, even in the basic implementation. However, their biometric performance varies strongly, which can be explained by the effort involved in calculating the score. As expected, the correlation coefficient provides the best performance.

There is no difference in performance between the Euclidean distance and the sum of squared differences. The additional square root operation of the Euclidean distance affects the score distributions, but not the relation of them. Hence, the error rates of all operating points are equal for both image distance functions. The inequality of the EER in table 8.1 is due to the error in the EER calculation. Consequently, a continuous investigation of both distance functions does not contribute to the analysis.

The biometric performance with DB3 is lower than with DB2. This can be explained by the higher difficulty level of DB3. In addition to more rotation and displacement, this database contains specially dried and moistened samples. Furthermore, no visual inspection was made for this database. Nevertheless, the outcomes with DB3 are consistent and show similar relations between the image distance functions as with DB2. DB3 can therefore be used for control tests as intended.

As a result of the insights, the further analysis focuses on the following three distance functions:

- *euclid globalN*
- *normCC*
- *corrCoeff*

8.2.2 INV2 - Image role pattern

Outline

The impact of the image role pattern on the biometric performance is documented below. This investigation includes a CAE test for each of the nine pattern presets:

- *1_T03_imageRolePattern_random1 ...*
  1_T11_imageRolePattern_random9

The investigation is carried out based on the correlation coefficient. This distance measure is the most comprehensive approach and provides the best performance yet. Investigations like this one, where the impact of the image distance function is not of interest, can thus be focused on the actual parameter.

Biometric performance

Table 8.4 shows the biometric performance for each pattern preset.

Table 8.4: INV2 - Biometric performance with different image role patterns

Image role pattern	EER
FVC_DB2_880_4e4v_random1	22.2%
FVC_DB2_880_4e4v_random2	22.0%
FVC_DB2_880_4e4v_random3	21.8%
FVC_DB2_880_4e4v_random4	22.7%
FVC_DB2_880_4e4v_random5	22.3%
FVC_DB2_880_4e4v_random6	22.7%
FVC_DB2_880_4e4v_random7	21.6%
FVC_DB2_880_4e4v_random8	21.9%
FVC_DB2_880_4e4v_random9	21.8%

The following observations can be made:

- The best EER can be achieved with *FVC_DB2_880_4e4v_random7*.
- The worst EER can be achieved with *FVC_DB2_880_4e4v_random4* and *FVC_DB2_880_4e4v_random6*.

Computational effort

The image role pattern has no impact on the correlation operations.

Insights gained

The image role pattern has a minor impact on the biometric performance. The visual inspection for this phase can therefore be rated as successful.

The seventh pattern is used in the further analysis of this phase. The sixth one is used as control test pattern.

8.2.3 INV3 - Reduction of the CAE test duration

Outline

The aim of this investigation is to shorten the CAE test duration in this phase. This includes the following CAE tests:

- *1_T12_durationReduction_noParfor*
- *1_T13_durationReduction_parfor*
- *1_T14_durationReduction_impostorSkip_1 ...*
  1_T14_durationReduction_impostorSkip_16
- CT P & CT DB for T14

The investigation is carried out based on the correlation coefficient.

The first measure is the utilization of the parallelization capability of MATLAB®.

The second measure is the reduction of the impostor comparisons. A biometric test under the defined comparison scheme of this phase comprises the following number of comparisons:

- Total comparisons: 193,600
  - Genuine comparisons: 1,760
  - Impostor comparisons: 191,840

The number of impostor comparisons is much higher than the number of genuine comparisons and therefore offers a possibility to shorten a biometric test. The score distributions are Gaussian. With respect to the number of genuine comparisons, the skipping of impostor comparisons is not expected to change the characteristic of the distribution. However, due to the finite number of comparisons, the outcomes are affected. Consequently, this measure must be evaluated in terms of its impact on the biometric performance.

In order to weight the volunteers equally, the following scenarios are investigated:

- 100% impostor comparisons
    - Each verification image per volunteer is used for impostor comparisons.
- 50% impostor comparisons
    - Two of four verification images per volunteer are used for impostor comparisons.
- 25% impostor comparisons
    - One of four verification images per volunteer is used for impostor comparisons.
- 12.5% impostor comparisons
    - One of four verification images of every second volunteer is used for impostor comparisons.
- 6.75% impostor comparisons
    - One of four verification images of every fourth volunteer is used for impostor comparisons.

CAE test duration & biometric performance

Table 8.5 summarizes the outcomes of this investigation[19].

Table 8.5: INV3 - CAE test durations

CAE test configuration	CAE test duration	EER
Without parallelization, 100% impostor comparisons	16.5h	21.6%
Parallelization, 100% impostor comparisons	2.68h	21.6%
Parallelization, 50% impostor comparisons	1.35h	21.9%
Parallelization, 25% impostor comparisons	0.69h	23.1%
Parallelization, 12.5% impostor comparisons	0.35h	23.0%
Parallelization, 6.75% impostor comparisons	0.18h	22.9%

The following observations can be made:

- A parallelization shortens the CAE test duration by about a factor of 6, which corresponds to number of physical CPU[20] cores.
- A skipping of impostor comparisons also shortens the duration, but it affects the biometric performance. The maximum EER differences between a complete and a reduced set are given in table 8.6 for the main test and the control tests.

Table 8.6: INV3 - EER difference in main and control tests, *iC*: impostor comparison

CAE Test	Maximum EER difference *max(EER 100% iC – EER reduced iC)*
Main test	-1.5%
CT P	-0.3%
CT DB	+0.7%

[19] The durations are measured with an AMD Ryzen 5 1600X Six-Core Processor with 3.60 GHz together with 16.0 GB RAM on Windows 10 (64-Bit).
[20] CPU - **C**entral **P**rocessing **U**nit

Insights gained

A parallelization is recommended. Without this, MATLAB® runs the CAE in a single process on just one CPU core. Furthermore, the degree of parallelization can be configured through the number of processes. Together with the execution of several MATLAB® instances, this enables an adjustment of the applied resources to the current needs.

The reduction of the number of impostor comparisons also shortens the execution time, but it affects the biometric performance. A correlation between the error rates and the amount of reduction cannot be observed. In addition, the impact on the biometric performance is less in the control tests and shows the opposite trend with DB3. This can therefore be explained by the finite number of comparisons. Remaining outliers are weighted more heavily and the impostor distribution is changed slightly, which affects the EER.
This makes the skipping of impostor comparisons a valid measure in the further analysis as long as the reference test used for the outcome evaluation is based on the same degree of reduction. The control tests can be based on a higher reduction than the main test, but must be consistent in itself. Only the reduction scenarios described above are used.

These two measures offer the possibility to scale a CAE test with regard to the resources. Their use is flexible in the further analysis and documented in the external PowerPoint file.

8.3 Part 2 - Optimization of the biometric performance

8.3.1 INV4 - Basic rotation

Outline

The impact of rotation on the biometric performance and the computational effort is documented below. The investigation includes the following CAE tests:

- *1_T15_basicRotation_idaSweep_reference*
- *1_T16_basicRotation_3-3-1_idaSweep*
- *1_T17_basicRotation_6-6-1_idaSweep*
- *1_T18_basicRotation_9-9-1_corrCoeff*
- *1_T19_basicRotation_12-12-1_corrCoeff*
- *1_T20_basicRotation_15-15-1_corrCoeff*
- *1_T21_basicRotation_6-6-2_corrCoeff*
- *1_T22_basicRotation_6-6-3_corrCoeff*
- *1_T22a_basicRotation_6-6-6_corrCoeff*
- CT P for T15 and T16
- CT DB for each CAE test

The investigation was initially carried out based on the following three image distance functions:

- *euclid globalN*
- *normCC*
- *corrCoeff*

Due to the outcomes and the duration of the first tests, the further investigation was carried out based on the correlation coefficient.

Rotation is implemented by rotating the enrollment template using the MATLAB® function *imrotate*. The image is rotated around its center using a bicubic interpolation. The rotated image is large enough to contain the entire rotated image. Thus, it is larger than the original image. Please be referred to the MATLAB® documentation for more information about *imrotate*.

The CAE implementation of rotation enables a configuration of the maximum clockwise rotation, the maximum counterclockwise rotation and the step size in degree. The rotation range examined, which is configured by this parameter set, is simply referred to as *rotation* in the following. A higher rotation means therefore a larger rotation range considered.

Biometric performance

For reasons of comprehensibility, the impact on the biometric performance is described using the outcomes of the correlation coefficient. Subsequently, the different image distance functions are compared, followed by the analysis of various step sizes.

Table 8.7 shows the biometric performance of the correlation coefficient for different rotations.

Table 8.7: INV4 - Biometric performance when considering rotation - *corrCoeff*

Image distance function	Rotation (1° steps)	EER	
		DB2	DB3
corrCoeff	*noRotation*	23.1%	30.6%
	-3° ... +3°	21.1%	29.5%
	-6° ... +6°	20.1%	28.9%
	-9° ... +9°	20.2%	28.8%
	-12° ... +12°	20.2%	28.8%
	-15° ... +15°	20.9%	28.6%

The following observations can be made:

- With rotation, an improvement in the EER can be observed for both databases. The improvement is higher with DB2 than with DB3.
- The positive impact decreases with higher rotations.
  - Compared to the best configuration with DB2, a higher rotation leads to a deterioration in the EER.

This can be explained by the development of impostor and genuine distribution. The error rates are defined by the overlap of these distributions. Thus, a deterioration of the biometric performance corresponds to a moving of the distributions towards each other. The following figure 8.2 illustrates this by using the change in the mean values of the two distributions. A consideration of rotation leads to more correlation operations and thus to higher matching scores. An improvement in the EER can be observed as long as the mean of the genuine distribution increases more than the mean of the impostor distribution. With regard to figure 8.2, where the change in the mean values to the previous rotation is shown, the EER is improved as long as the blue curve is above the orange curve.

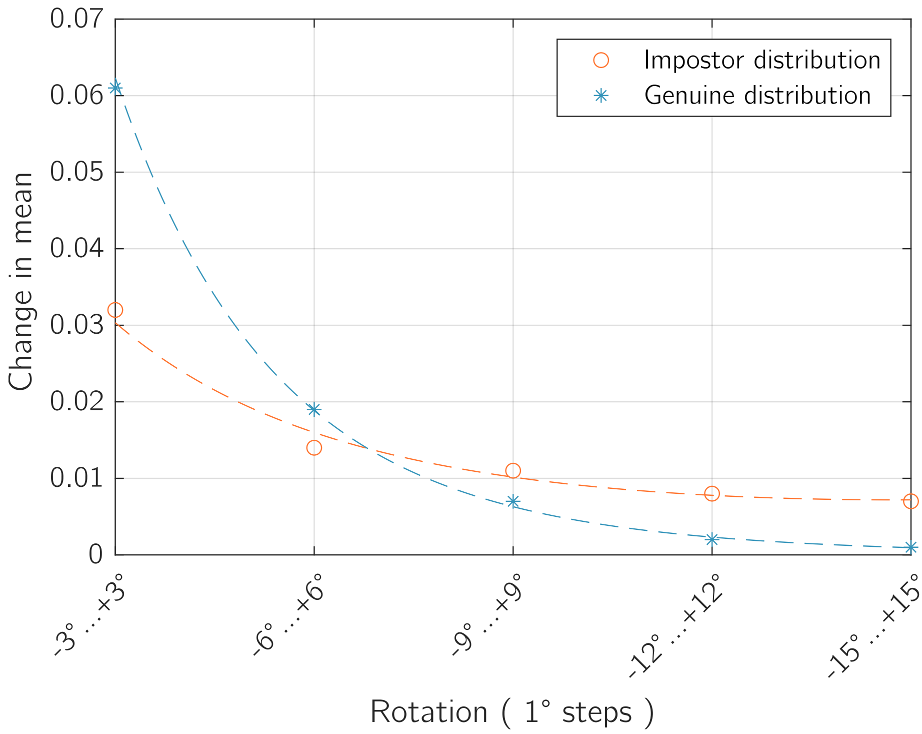

Figure 8.2: INV4 - Change in the mean values with DB2,
the dashed curve shows a fitting of the measurement points by an exponential function

This effect can be observed with both databases. Table 8.7 shows a further improvement for higher rotation with DB3. However, the development of the mean values is similar to that of DB2. Consequently, a deterioration of the biometric performance is expected for higher rotations than ±15°.

Table 8.8 shows the biometric performance of the different image distance functions when considering rotation.

Table 8.8: INV4 - Biometric performance when considering rotation

Image distance function	Rotation (1° steps)	EER	
		DB2	DB3
euclid globalN	*noRotation*	31.0%	36.4%
	-3° ... +3°	27.3%	36.0%
	-6° ... +6°	26.7%	35.6%
normCC	*noRotation*	42.6%	37.0%
	-3° ... +3°	38.4%	34.1%
	-6° ... +6°	37.1%	33.4%
corrCoeff	*noRotation*	23.1%	30.6%
	-3° ... +3°	21.1%	29.5%
	-6° ... +6°	20.1%	28.9%

The following observations can be made:

- The image distance functions *euclid globalN* and *normCC* show similar tendencies as *corrCoeff*. The described effect of rotation on the distributions is confirmed.

So far, all rotations are based on a step size of one degree. Table 8.9 on the next page shows the biometric performance in dependency to the step size for the correlation coefficient.

Table 8.9: INV4 - Biometric performance for various rotation step sizes

Image distance function	Rotation step size (-6° … +6°)	EER	
		DB2	DB3
corrCoeff	1°	20.1%	28.9%
	2°	20.4%	29.0%
	3°	20.7%	28.9%
	6°	21.3%	29.3%

The following observations can be made:

- An increase of the step size leads to a deterioration in the biometric performance with both databases. This can be explained by the missing of actual matching scores at the rotation steps not taken into account.

Computational effort

Table 8.10 summarizes the outcomes concerning the computational effort.

Table 8.10: INV4 - Computational effort when considering rotation

Rotation (1° steps)	Number of rotation steps	C-OP factor
noRotation	1	1
-3° … +3°	7	7.5
-6° … +6°	13	14.8
-9° … +9°	19	22.8
-12° … +12°	25	31.5
-15° … +15°	31	41.0

The following observations can be made:

- The C-OPs increase with a higher factor than the number of rotation steps.

This is due to the increased size of the enrollment template. As mentioned in the outline of this investigation, the enrollment template is larger after rotating. Thus, more offsets are taken into account, which means a higher number of correlation operations.

Insights gained

The consideration of rotation improves the biometric performance, but comes along with an enormous increase in the computational effort. The number of correlation operations is multiplied by a factor higher than the number of the rotation steps considered.
With every further rotation step, the extent of improvement decreases. At a certain point, the performance is impaired by every further rotation. This can be explained by a higher increase in the impostor scores than the genuine scores.
Furthermore, a step size higher than one degree reduces the improvement.

The three image distance functions show a similar development when rotation is taken into account.

The performance improvement is less with DB3. This is expected because the collection process of this database allows more rotation of the fingerprints compared to DB2.
With DB3 and a rotation of $\pm 6°$, the normalized cross correlation performs better than the Euclidean distance. This is a difference to DB2, where the Euclidean distance shows generally a higher performance. Nevertheless, the correlation coefficient shows the best performance for both databases.

For further investigations, rotation is only taken into account if a dependency of the investigated parameter on rotation is expected.

8.3.2 INV5 - Feature size

Outline

The impact of the feature size on the biometric performance and the computational effort is documented below. The investigation includes the following CAE tests:

- *1_T23_featureSize_noRot_8px-72px_4pxStep*
- *1_T24_featureSize_3-3-1_24px-56px_16pxStep*
- CT P & CT DB for T23

With the comparison scheme of this phase, a verification template consists of one feature. Thus, a variation in the feature size corresponds to a variation in the verification sample size. The defined maximum size of a verification sample is 72 px × 72 px in this phase.

The CAE implementation of the cropping operation enables a configuration of the edge length. The parameter sweep is set up as follows:

- Sweep of parameter *feature size*
    - From 8 px to 72 px in steps of 4 px for each of the three distance functions

All features of the same image, regardless of their size, are based on the same cropping center. This is shown in figure 8.3 with an example image. The aspect ratio of the feature is one to one throughout this investigation.

Figure 8.3: INV5 - Examples of feature sizes, fingerprint images are based on [Mai+02a, DB2]

In the second CAE test, the dependency of rotation on the feature size is examined using the correlation coefficient and a reduced parameter sweep.

Biometric performance

Figure 8.4 shows the EER for each configuration of the sweep described above. The gray trace provides a relation to the amount of information by showing the pixel count for each feature size.

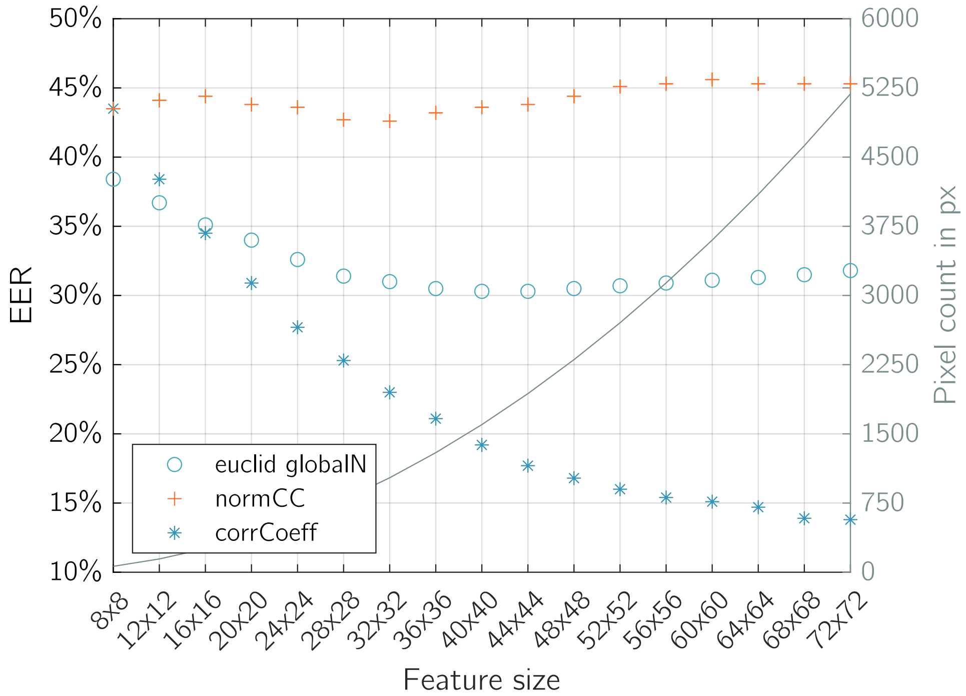

Figure 8.4: INV5 - Biometric performance for various feature sizes

The following observations can be made:

- The EER traces of the image distance functions do not show a consistent relation to the pixel count, especially for large features. Consequently, a higher amount of information does not automatically lead to an improvement in performance.
- An increase in the feature size leads to an improvement in the EER up to a certain size, which is different for each of the image distance functions. For *euclid globalN* and *normCC*, the performance is slightly decreasing after that size. For *corrCoeff*, the decrease is expected to be outside of the sweep range.

Table 8.11 on the next page summarizes the feature sizes with the best performance. For the outcomes in that table, the following observations can be made:

- The features sizes with the best EER are consistent for the two databases. The difference for *normCC* follows the previous insight that this image distance function is more advantageous with DB3 than with DB2.
- The pattern control test reveals the same best feature sizes as the main test.

Table 8.11: INV5 - Feature sizes with the best biometric performance

Image distance function	Feature size with the best EER	
	DB2 & DB2 (CT P)	DB3
euclid globalN	40px × 40px	40px × 40px
normCC	32px × 32px	40px × 40px
corrCoeff	72px × 72px	68px × 68px

The effect of the parameter *feature size* on the score distributions is explained in the following. The development in the scores is reverse to that of *rotation*. As the amount of information in the verification template increases, the template becomes more selective, the scores are decreased. The performance is improved as long as the mean of the impostor distribution decreases more than the mean of the genuine distribution. The following figure 8.5 illustrates this using the outcomes of the Euclidean distance with DB2. Please note that the change in mean is shown as an absolute value. Thus, the EER is improved as long as the blue curve is below the orange curve.

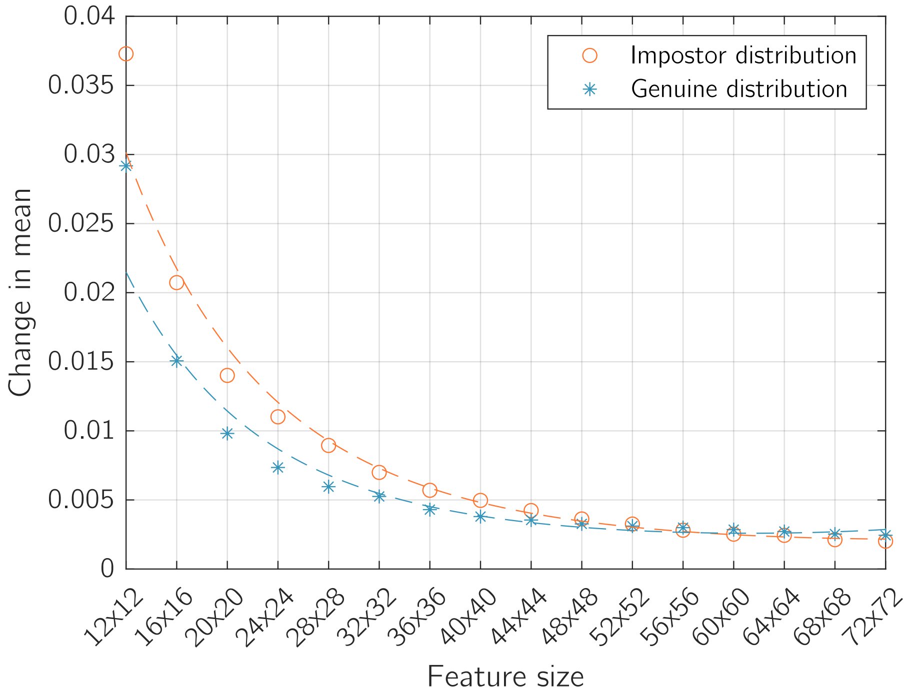

Figure 8.5: INV5 - Change in the mean values with DB2, the dashed curve shows a fitting of the measurement points by an exponential function

As opposed to the development caused by *rotation* (figure 8.2), a larger change in the mean value means a larger decrease of the scores in the figure above.

Using the correlation coefficient with DB2, the performance is continuously improved throughout the sweep, even for the largest feature size. It is expected that the described effect leads to a performance deterioration outside the sweep range. The development of the performances with DB3 confirms this expectation.

Table 8.12 shows the EER improvement through considering rotation in dependency to the feature size.

Table 8.12: INV5 - EER improvement through considering rotation

Feature size	EER improvement From *noRotation* to (-3° ... 3° in 1° steps)
24px × 24px	1.7%
40px × 40px	2.6%
56px × 56px	3.9%

The following observations can be made:

- The improvement is greater with larger features. This can be explained by the rotation operation itself. Outer pixels in an image are much more affected by rotation. Consequently, a compensation of rotation improves the performance more when larger features are used.

Computational effort

As described in section 7.3, the duration of one comparison is calculated by

$$t_{Comparison} = t_{C\text{-}OP} \cdot n_{C\text{-}OP} \quad .$$

Both factors depend on the feature size. Thus, an evaluation of the computational effort only concerning the number of correlation operations is not sufficient in this investigation.

Figure 8.6 on the next page shows the duration of one C-OP as measured on the MCU. The gray trace provides the number of C-OPs per comparison. The resulting duration per comparison is shown in the following figure 8.7.

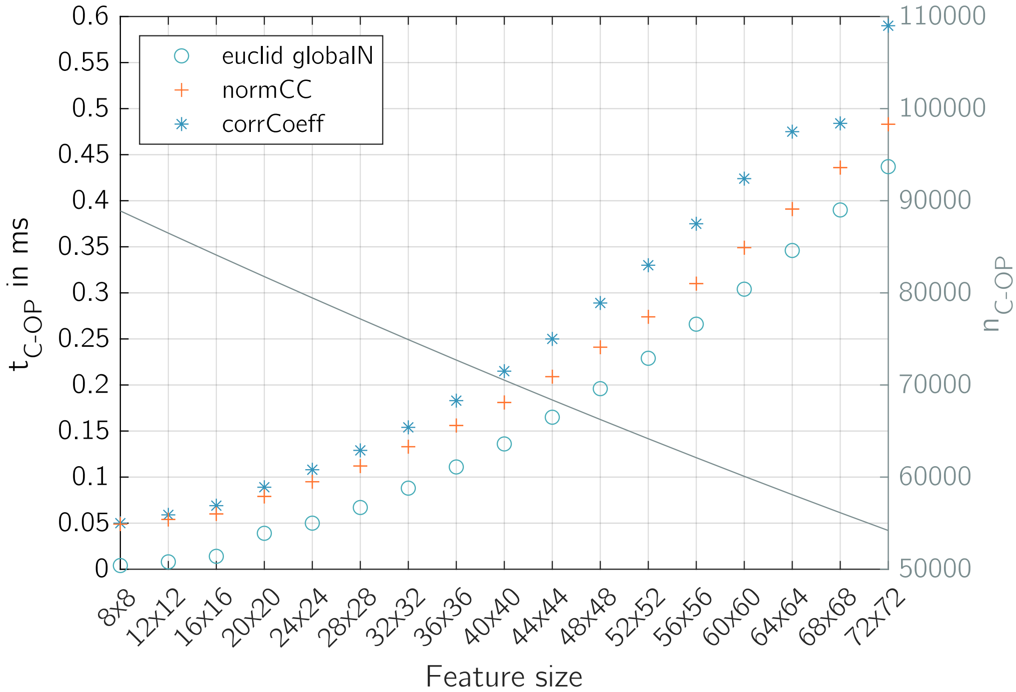

Figure 8.6: INV5 - Duration of one C-OP for various feature sizes, the number C-OPs are based on the configuration of T23 and the comparison scheme of this phase

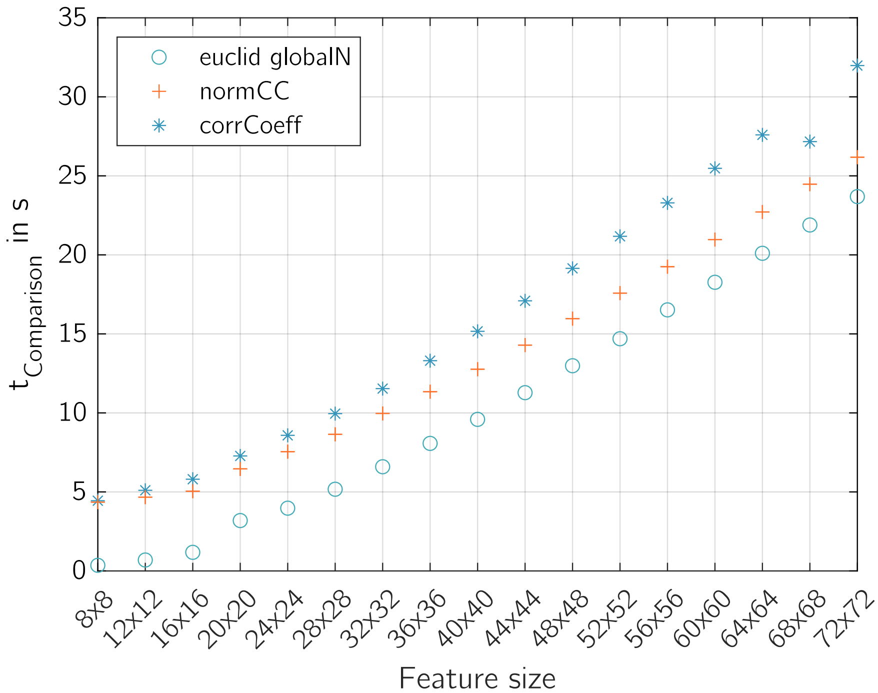

Figure 8.7: INV5 - Duration of one comparison for various feature sizes, the timings are based on the configuration of T23 and the comparison scheme of this phase

The following observations can be made:

- The durations $t_{C\text{-}OP}$ and $t_{Comparison}$ increase with higher feature sizes. Due to the decrease of $n_{C\text{-}OP}$, the slope of $t_{Comparison}$ is lower than the slope of $t_{C\text{-}OP}$. This is consistent for the three image distance functions.
- As already indicated by the underlying equations of the distance functions, *corrCoeff* lasts the longest, followed by *normCC* and *euclid globalN*. This applies to all feature sizes.
- The slope of the durations is not equal for all distance functions. With the increase of the feature size, the duration of *corrCoeff* increases the most, followed by *euclid globalN* and *normCC*. This is the same for both charts because $n_{C\text{-}OP}$ is constant for one feature size.
- The outlier with *corrCoeff* at a feature size of 68 px × 68 px is due to unexpected optimization behavior of the compiler of the MCU IDE. For reasons of time, the cause is not investigated further in this project.

In summary, the computational effort for one comparison increases with the feature edge length in an approximately linear way.

Insights gained

The development in the biometric performance can be explained by non-linear distortion of the captured fingerprint. With smaller features, the amount of information is restricted, but a good alignment can be assured. With larger features, the correlation suffers from non-linear distortion despite the increased amount of information.

The three image distance functions response differently to that. The correlation coefficient provides the best performance. The gap to the other distance functions grows with higher features sizes.

The following examples expound the relation of biometric performance and computational effort using the outcomes of the correlation coefficient.
For an edge length of 72 px compared to 36 px, the EER improves about 7.5% and the number of C-OPs increases by a factor of approximately 2.4.
Another example using the edge lengths of 56 px and 28 px exhibits a greater EER improvement with approximately the same increase factor for the number of C-OPs.

Therefore, the selection of the feature size is a tradeoff between biometric performance and computational effort. Please note that the verification template is composed of one feature in this phase. The pixel count grows quadratically with the feature edge length. Thus, a doubling of the feature edge length corresponds to a quadrupling of the feature count. Consequently, a statement to the optimal feature size depends strongly on the performance improvement when more than one feature is used.

The feature size of 36 px × 36 px is selected for further investigations. With regard to a desired independence of the feature size, this is a size that guarantees a sufficient amount of information for all image distance functions.

8.3.3 Interim conclusion

Development of the score distributions

The last two investigations make the draw of an interim conclusion possible. The parameters can be categorized into two types concerning their effect on the score distributions:

- *Score-increasing type*
- *Score-decreasing type*

As described in the investigations of the parameters *rotation* and *feature size*, the biometric performance is improved as long as the distance between the distributions grows. Figure 8.8 and 8.9 show one example of both types using the correlation coefficient.

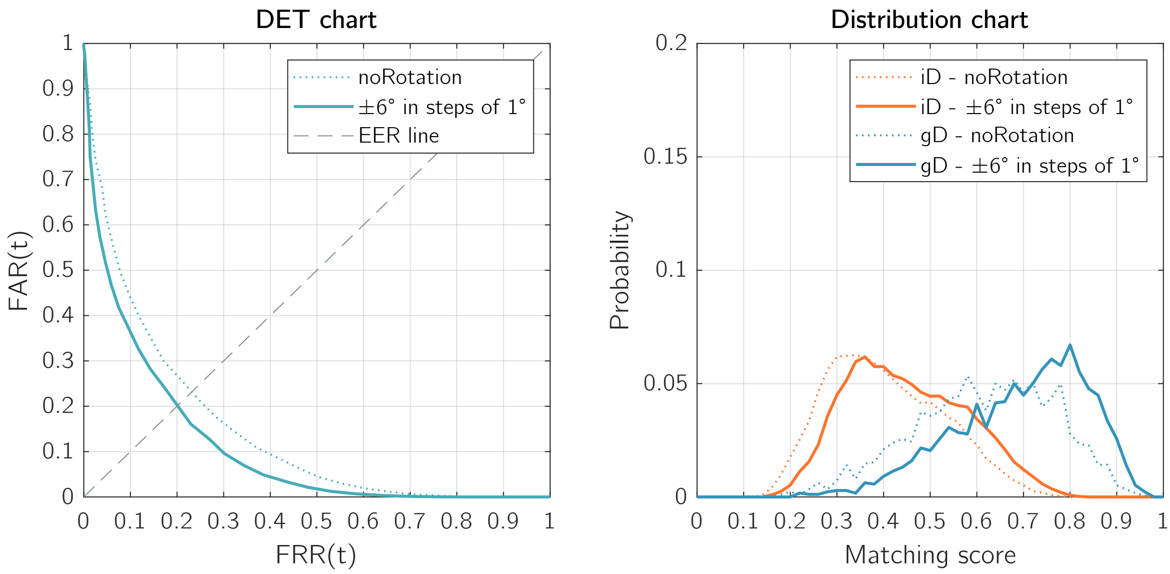

Figure 8.8: Parameter *rotation* - score-increasing effect

Figure 8.8 shows the score-increasing effect when considering rotation.

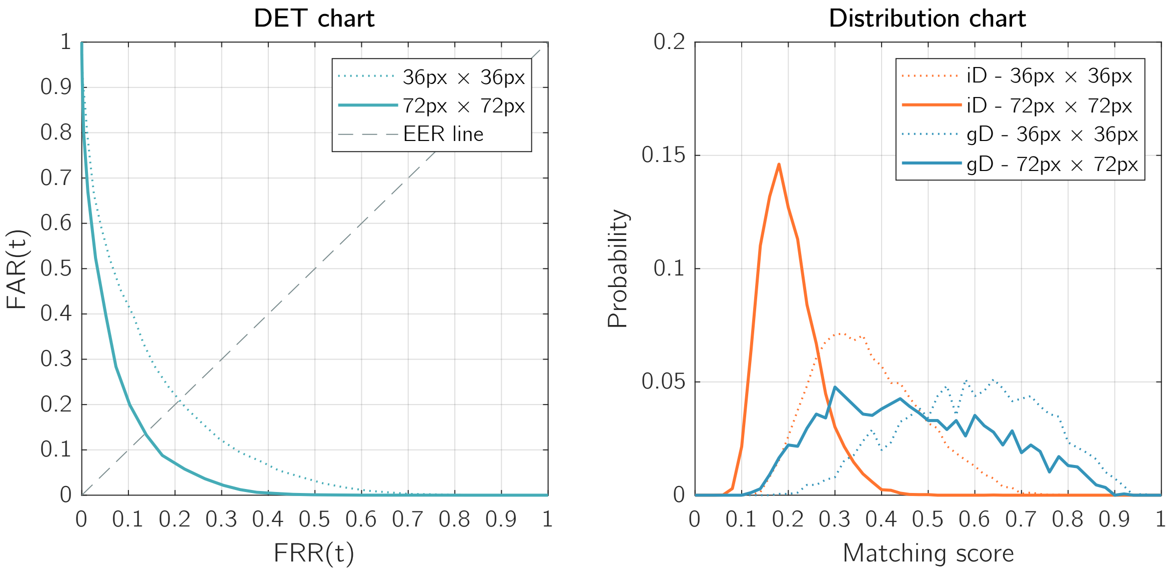

Figure 8.9: Parameter *feature size* - score-decreasing effect

Figure 8.9 shows the score decreasing-effect when expanding the feature size.

Both DET charts indicate an improvement in the system performance. The corresponding distribution charts show the effects mentioned above, which have a direct impact on the mean of the distributions. The standard deviation is indirectly affected by the change in the mean values within the limited score range.

This characteristic is expected for all parameters that have a direct impact on the computation of the matching score. Due to the identical processing of genuine and impostor comparisons, the score distributions do not change independently of each other. A parameter that improves the performance by simultaneously increasing the genuine scores and decreasing the impostor scores is not expected to be existent. Hence, an evaluation of the outcomes is only reasonable for both distributions together.

Performance of the image distance functions

All outcomes up to this point show the correlation coefficient as the best image distance function for both databases, followed by the Euclidean distance and the normalized cross correlation. The two latter show a different performance with the two databases compared to the correlation coefficient with the corresponding database:

- The Euclidean distance is worse with DB3 compared to DB2.
- The normalized cross correlation is better with DB3 compared to DB2.

Concerning the effects on the score distributions described above, the image distance functions show a consistent reaction to the parameters. However, the intensity of this reaction is different. This can be explained by the characteristic of the functions themselves, but also by their performance. For example, an improvement observed around an EER of 40% cannot be expected to have the same extent around 20%.
Concerning the computational effort, each image distance function shows a similar relation to the feature size. With larger features, the relative difference between them becomes smaller.
The correlation coefficient shows the best performance for both databases. Its computational effort is the highest of the image distance functions, but is acceptable in relation to the performance. Due to the consistency of the reaction of the image distance functions to the parameters, this is not expected to change in the further analysis. Consequently, the correlation coefficient is assessed to be the appropriate image distance function for this project.

However, the outcomes of the normalized cross correlation and the Euclidean distance contribute to the analysis process and help to understand the effect of the parameters under investigation. Consequently, these two image distance functions are further taken into account for this part of the first phase.

Documentation of further investigations

In order to focus on the parameter under investigation in the following, some changes are intended for the documentation. The following observations are assumed as given because they are expected to remain constant for the analysis:

- The performance with DB2 is generally better than with DB3.
- The impact of the current parameter on the biometric performance is less with DB3 than with DB2.
- The relation between the image distance functions remain as described above.

In the following, the documentation within the thesis takes place only in terms of the impact of the current parameter. Observations regarding the performance ratio of the databases or the image distance functions are only mentioned if the assumptions above are refuted. In addition, the outcomes of the control tests are only mentioned if they contradict the outcomes of the main test.

Nevertheless, all outcomes are documented in the external database file.

8.3.4 INV6 - Feature shape (aspect ratio)

Outline

The impact of the parameter *feature shape* on the biometric performance and the computational effort is documented below. The investigation includes the following CAE tests:

- *1_T25_featureShape_1296pixel*
- *1_T26_featureShape_576pixel_corrCoeff*
- CT P for T25
- CT DB for T25 & T26

In the previous investigation, the amount of information contained in the features are examined. With a constant aspect ratio of 1:1, the pixel count of a feature is varied.

This investigation targets the reverse scenario. With a constant pixel count, the aspect ratio of a feature is varied. The basis is a 36 px × 36 px feature, which contains 1296 pixels. The shape variations are shown in figure 8.10 using an example image. The aspect ratios 16:1 and 1:16, which are also to be examined, are not illustrated for reasons of size.

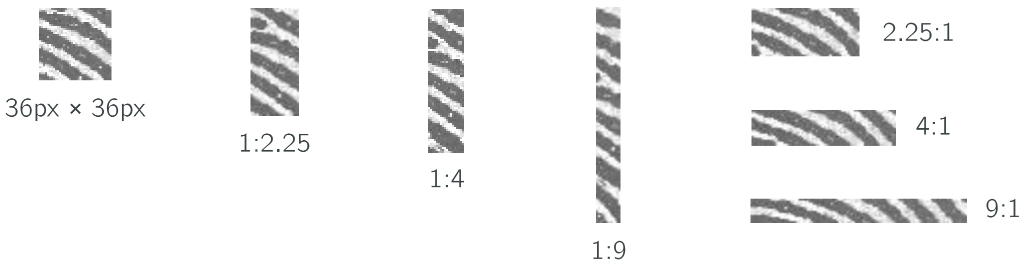

Figure 8.10: INV6 - Examples of aspect ratios, fingerprint images are based on [Mai+02a, DB2]

These aspect ratios were selected with the premise to avoid rounding the edge lengths. A constant pixel count is guaranteed as long as the edges are shortened respectively extended by the same factor.

In the second CAE test, the dependency of the parameter impact on the pixel count is examined using a 24 px × 24 px as a basis.

A feature with a longer vertical edge is referred to as a *vertical feature* in the following. A feature with a longer horizontal edge is referred to as a *horizontal feature*.

Biometric performance

Table 8.13 shows the biometric performance for vertical features using the correlation coefficient.

Table 8.13: INV6 - Biometric performance for vertical features

Feature aspect ratio	Feature size	EER - *corrCoeff*
1:1	36px × 36px	21.1%
1:2.25	24px × 54px	21.4%
1:4	18px × 72px	22.0%
1:9	12px × 108px	21.8%
1:16	9px × 144px	22.2%

The following observations can be made:

- This variation leads to a deterioration in the EER compared to square-shaped features.

Table 8.14 shows the biometric performance for horizontal features using the correlation coefficient.

Table 8.14: INV6 - Biometric performance for horizontal features

Feature aspect ratio	Feature size	EER - *corrCoeff*
1:1	36px × 36px	21.1%
2.25:1	54px × 24px	19.7%
4:1	72px × 18px	18.8%
9:1	108px × 12px	19.9%
16:1	144px × 9px	20.1%

The following observations can be made:

- Each variation leads to an improvement in the EER compared to square-shaped features. The best biometric performance is achieved with an aspect ratio of 4:1.

The control tests confirm the tendency, but differ in terms of the improvement for the various aspect ratios. Table 8.15 shows the biometric performance of all test forms for the best aspect ratios. Furthermore, the different image distance functions are taken into account.

Table 8.15: INV6 - EER comparison of main and control tests

Image distance function	Feature aspect ratio	EER		
		DB2	DB2 (CT P)	DB3
euclid globalN	1:1	30.7%	29.6%	35.9%
	2.25:1	30.3%	28.6%	35.7%
	4:1	31.0%	29.4%	35.8%
normCC	1:1	43.2%	40.7%	36.5%
	2.25:1	43.2%	40.1%	36.3%
	4:1	44.0%	40.4%	36.9%
corrCoeff	1:1	21.1%	21.1%	28.8%
	2.25:1	19.7%	19.8%	27.6%
	4:1	18.8%	18.8%	28.1%

The following observations can be made:

- All image distance functions show an improvement in the EER for the aspect ratio of 2.25:1.
- A further improvement with an aspect ratio of 4:1 can only be observed using *corrCoeff* with DB2. The outcomes with DB3 and the outcomes of the other distance functions contradict this.

The general tendency of improvement with horizontal features can be explained by the shape of the finger. The fingerpint as a whole has a longer vertical edge. A horizontal features outside the core tends to contain a greater change in curvature of the ridges than a vertical feature at the same position. This can also be seen in figure 8.10 to some extent. More curvature means more distinctive information, which leads to better distinction. Thus, the biometric performance is improved.

The second CAE test confirm the outcomes of the first one for a reduced pixel count.

Computational effort

Table 8.16 summarizes the outcomes concerning the computational effort. The number of correlation operations is only shown for DB3 due to the square-shaped images in this database. With DB2, a difference in the computational effort between vertical and horizontal features can be observed. This does not correspond to the use case of square-shaped sensors.

Table 8.16: INV6 - Computational effort for various feature aspect ratios

Feature aspect ratio	C-OP factor - DB3
1:1	1
1:2.25 / 2.25:1	0.974
1:4 / 4:1	0.923
1:9 / 9:1	0.794
1:16 / 16:1	0.653

The following observations can be made:

- An adapted feature aspect ratio leads to a reduction of the C-OPs. The reduction is greater with a larger difference between width and height of the feature. This can be explained by a smaller search range with such shaped features.

Insights gained

The parameter *feature shape* is a score-decreasing type. The greater the difference between width and height of the feature, the lower are the means of the distributions.

With the same pixel count, a better biometric performance can be observed for horizontal features compared to vertical features.

The change of the feature aspect ratio generally leads to a decrease in the computational effort compared to square-shaped features.

Consequently, with a feature aspect ratio of 2.25:1, the biometric performance is improved and the computational effort is slightly reduced.

8.3.5 INV7 - Resolution

Outline

The impact of the parameter *resolution* on the biometric performance and the computational effort is documented below. The investigation includes the following CAE tests:

- *1_T27_resolution_noScaling* (48x48)
- *1_T28_resolution_downScaling1.5* (48x48)
- *1_T29_resolution_downScaling2* (48x48)
- *1_T30_resolution_36x36_noScaling*
- *1_T31_resolution_36x36_downScaling1.5*
- *1_T32_resolution_36x36_downScaling2*
- *1_T33_resolution_72x72_noScaling*
- *1_T34_resolution_72x72_downScaling1.5*
- *1_T35_resolution_72x72_downScaling2*
- CT DB for T27-T29

As described in the analysis of the conceptual formulation in chapter 3, the resolution must be analyzed by scaling down the images. The following resolutions are investigated:

- 250 dpi
- 375 dpi
- 500 dpi

The resolution of the FVC databases is 500 dpi. The corresponding downscaling operations are implemented in the CAE using the MATLAB® function *imresize*. The image is resized using a bicubic interpolation. Please be referred to the MATLAB® documentation for more information about *imresize*.

A comparison is only reasonable if enrollment and verification template are identical in resolution. Hence, the downscaling operation is applied consistently to all images for one test configuration.

The investigation is carried out based on the following feature sizes:

- 36 px × 36 px
- 48 px × 48 px
- 72 px × 72 px

Biometric performance

Table 8.17 shows the biometric performance based on a feature size of 48 px × 48 px in the resolutions to be investigated.

Table 8.17: INV7 - Biometric performance for various resolutions

Resolution	EER		
	euclid globalN	*normCC*	*corrCoeff*
500dpi	30.6%	44.4%	16.8%
375dpi	27.6%	39.8%	15.2%
250dpi	27.2%	38.0%	15.4%

The following observations can be made:

- The downscaling operation results in an improvement in the EER for all image distance functions compared to the original resolution.
- The best performance is achieved at 250 dpi using *euclid globalN* and *normCC*. When using *corrCoeff* a downscaling to 250 dpi leads to a deterioration compared to 375 dpi.

A possible explanation to this improvement is the interpolation within the scaling operation. The bicubic interpolation is taking into account the nearest 4-by-4 neighborhood to calculate the new pixel value. This corresponds to a low-pass filtering. At the same time, when scaling down by a factor of two, the area of four pixels is represented by one pixel after the operation. This conversion contributes to a pixel-wise comparison and compensates possible information loss. Furthermore, unnecessary information in the fingerprint like sensor noise are removed by the filtering.

Table 8.18 summarizes the dependency of the biometric performance on the feature size in relation to the resolution.

Table 8.18: INV7 - Dependency on the feature size

Original feature size	Resolution	Feature size after scaling	EER		
			euclid globalN	*normCC*	*corrCoeff*
36px × 36px	500dpi	36px × 36px	30.7%	43.2%	21.1%
48px × 48px	375dpi		27.6%	39.8%	15.2%
72px × 72px	250dpi		28.2%	40.2%	12.6%

The following observations can be made:

- The best resolution in terms of the image distance functions is reverse to the previous table. When using *corrCoeff* a further improvement can be observed for 250 dpi. When using *euclid gobalN* and *normCC* a downscaling to 250 dpi leads to a deterioration compared to 375 dpi.

These outcomes show the already observed dependency of the image distance functions on the feature size. The correlation coefficient shows the best performance with a feature size of 72 px × 72 px. The performance of the other distance functions deteriorates with that size. This confirms the beneficial effect of the downscaling operation as described above. Therefore, a comparison at a resolution of 250 dpi is recommended for all image distance functions.

Computational effort

The downscaling operation reduces the pixel count of enrollment and verification template. Consequently, the number of correlation operations as well as the duration of one correlation operation is affected. Table 8.19 summarizes the outcomes concerning the computational effort based on a feature size of 72 px × 72 px and the timings of the correlation coefficient.

Table 8.19: INV7 - Computational effort for various resolutions

Resolution	Feature size after scaling	$n_{C-OP,factor} \cdot t_{C-OP,factor} = t_{Comparison,factor}$
500dpi	72px × 72px	$1 \cdot 1 = 1$
375dpi	48px × 48px	$0.45 \cdot 0.49 = 0.22$
250dpi	36px × 36px	$0.25 \cdot 0.31 = 0.078$

The following observations can be made:

- The downscaling operation comes along with an enormous saving of computational effort. The number of the C-OPs as well as the duration of one C-OP are reduced by a factor of the same order of magnitude.

Insights gained

The downscaling of the images reveals the ideal way to meet the challenges of this project. In addition to improving the biometric performance, the computational effort can be significantly reduced. Furthermore, the memory required is less due to the decreased size of enrollment and verification template.

In addition, the downscaling enables an utilization of large feature sizes. The pixel count is reduced without decreasing the captured fingerprint area. Thus, feature sizes that ensure the best performance using the correlation coefficient can be managed with regard to the computational effort.

The parameter *resolution* is a score-increasing type. The higher the downscaling factor, the higher are the means of the distributions.

8.3.6 INV8 - Low-pass filtering

Outline

The impact of the parameter *low-pass filtering* on the biometric performance and the computational effort is documented below. The investigation includes the following CAE tests:

- *1_T36_lpf_reference*
- *1_T37_lpf_avg3*
- *1_T38_lpf_avg5*
- *1_T39_lpf_avg7*
- *1_T40_lpf_binom3*
- *1_T41_lpf_binom5*
- *1_T42_lpf_binom7*
- *1_T43_lpf_gaussian3*
- *1_T44_lpf_gaussian5*
- *1_T45_lpf_gaussian7*
- *1_T46_lpf_gaussian5_1.9*
- *1_T47_lpf_gaussian5_1.3*
- CT DB for T36 & T43-T45

The previous investigation shows the benefit of filtering unnecessary information in the fingerprint. The low-pass filtering, but without changing the resolution, is examined in the following.

The periodic ridge-valley pattern describes the information in a fingerprint. Thus, unnecessary information can be described by frequencies higher than the one of the pattern. In order to remove this frequencies, a linear low-pass filter can be applied.

The output pixel value of a filter is a weighted average of its own value and its neighborhood. The filter size defines the size of this neighborhood. The weighting defines the filter type. Please be referred to [BB16, p.89 ff.] for an introduction to filters in image processing.

The following filter types in sizes 3, 5 and 7 are implemented in the CAE:

- Simple average filter (box filter)
- Binomial filter
- Gaussian filter with a configurable cutoff frequency

Filtering is only reasonable when applied to enrollment and verification image in the same manner.

Biometric performance

Table 8.20 shows the biometric performance for all applied filters using the correlation coefficient.

Table 8.20: INV8 - Biometric performance for different low-pass filters - *corrCoeff*

Filter type	Filter size	EER - *corrCoeff*	
		DB2	DB3
None (reference)	-	21.1%	28.8%
Box	3	19.2%	-
	5	18.3%	-
	7	18.2%	-
Binomial	3	19.2%	-
	5	19.0%	-
	7	18.5%	-
Gaussian	3	19.1%	28.3%
	5	18.5%	29.3%
	7	18.0%	30.1%

The following observations can be made with DB2:

- The filter types, regardless of their size, improve the EER. The best performance is achieved with a Gaussian filter with a size of 7.

The following observations can be made with DB3:

- A Gaussian filter with a size of 5 or 7 deteriorates the EER compared to the reference. An improvement is achieved with a Gaussian filter with a size of 3.

Table 8.21 shows type and size of the filter with the greatest EER improvement for each of the three image distance functions.

Table 8.21: INV8 - Best filter configurations

Filter type	Filter size	Greatest EER improvement		
		euclid globalN	*normCC*	*corrCoeff*
Box / Binomial / Gaussian	3	X		
	5		X (Box, Gaussian)	
	7		X (Binomial)	X

The following observations can be made:

- The filter type with the greatest EER improvement varies for the different image distance functions. However, the best filter size for each image distance function is consistent between the filter types.

With higher filter sizes than the marked ones in the table above, a decrease in performance up to a deterioration compared to the reference can be observed.

The Gaussian type in the appropriate size provides the greatest improvement for each of the image distance functions. The further CAE tests of this investigation show a negligible effect of the cutoff frequency of the Gaussian filter.

Computational effort

The parameter has no impact on the number or on the duration of the correlation operations.

Insights gained

The filtering with an appropriate low-pass improves the biometric performance without affecting the computational effort of the comparison. The performance differences between the filter types are marginal, especially when using the correlation coefficient.

The development in the EER demonstrates the typical characteristic of the defined parameter types from the interim conclusion. As the filter size increases, an improvement is followed by a deterioration in the biometric performance. With low-pass filtering, this point is reached earlier for the Euclidean distance and the normalized cross correlation compared to the correlation coefficient. Furthermore, this point is reached earlier with DB3 for all image distance functions compared to DB2.

The parameter *low-pass filtering* is a score-increasing type. The higher the filter size, the higher are the means of the distributions.

8.3.7 INV9 - Normalization & gray-scale reduction

Outline

The impact of the normalization and the associated possible reduction of the gray-scale depth is documented below. The investigation includes the following CAE tests:

- *1_T48_normalization_reference*
- *1_T49_normalization_range255-8bit*
- *1_T50_normalization_range127-7bit*
- *1_T51_normalization_range63-6bit*
- *1_T52_normalization_range31-5bit*
- *1_T53_normalization_range15-4bit*
- *1_T54_normalization_range7-3bit*
- *1_T55_normalization_range3-2bit*
- *1_T56_normalization_range1-1bit*
- *1_T57_normalization_range1_rot_fs*
- *1_T58_normalization_range15_rot_fs*
- CT DB for T48-T58

The gray-scale depth of the fingerprint images is 8 bit. Therefore, the pixel intensity values can range from 0 to 255. Due to various reasons, for example a certain sensor characteristic or dry skin, the entire range is usually not used. Thus, the minimum and maximum intensity can be slightly different for each image, even for images of the same finger. A gray-scale normalization ensures the utilization of the entire range. Please be referred to [BB16, p.37 ff.] for more information about the intensity range and general image statistic.

The CAE implementation enables a gray-scale normalization that ensures a range from 0 to a desired maximum value. Figure 8.11 shows an example fingerprint before and after normalization. The original image is on the left. The pixel intensities of the middle image use the entire range, while those of the right one use a reduced range.

Intensity range: 93-253 Intensity range: 0-255 Intensity range: 0-63

Figure 8.11: INV9 - Examples of gray-scale normalization to a desired range, fingerprint images are based on [Mai+02a, DB2]

In addition, the effect of reducing the gray-scale depth are examined. This is done by adjusting the maximum intensity within normalization to a value below 255. For example, the image on the right in figure 8.11 features a 6 bit depth with a maximum intensity of 63. A reduction to one bit describes the binarization of an image.

These two operations are referred to as the parameters *normalization* and *gray-scale reduction*. Both are only reasonable when applied to enrollment and verification template in the same degree.

Biometric performance

Table 8.22 shows the biometric performance for the configurations of the parameter *normalization*.

Table 8.22: INV9 - Biometric performance for normalized images

Normalization / gray-scale depth	EER		
	euclid globalN	*normCC*	*corrCoeff*
Not normalized / 8bit (reference)	30.7%	43.2%	21.1%
Normalized / 8bit	26.6%	36.1%	21.1%

The following observations can be made:

- A high improvement can be achieved for *euclid globalN* and *normCC*. The performance of *corrCoeff* does not change through normalization.

The correlation coefficient takes into account relative distances. Consequently, as opposed to the other two image distance functions, the normalization does not affect the computation of the matching score.

Table 8.23 shows the biometric performance for the configurations of the parameter *gray-scale reduction* using the correlation coefficient.

Table 8.23: INV9 - Biometric performance for different gray-scale depths - *corrCoeff*

Normalization / gray-scale depth	EER - *corrCoeff*	
	DB2	DB3
Normalized / 8bit (reference)	21.1%	28.8%
Normalized / 7bit	21.1%	28.8%
Normalized / 6bit	21.1%	28.8%
Normalized / 5bit	21.1%	28.8%
Normalized / 4bit	21.3%	29.0%
Normalized / 3bit	21.6%	28.8%
Normalized / 2bit	23.5%	33.2%
Normalized / 1bit	22.3%	36.7%

The following observations can be made:

- No improvement in the EER can be achieved. Up to a reduction to 5 bit the performance is preserved.
- A reduction to 1 bit indicates an opposite tendency for the two databases compared to a reduction to 2 bit. While this binarization leads to an improvement with DB2, it leads to a further deterioration with DB3.

Table 8.24 shows the impact of binarization compared to a full gray-scale depth for all image distance functions.

Table 8.24: INV9 - Biometric performance for binarized images

Image distance function	EER - 8bit depth → EER - 1bit depth	
	DB2	DB3
euclid globalN	26.6% → 22.7%	32.9% → 43.4%
normCC	36.1% → 39.8%	35.9% → 42.0%
corrCoeff	21.1% → 22.3%	28.8% → 36.7%

The following observations can be made:

- Except for the Euclidean distance with DB2, the binarization leads to a deterioration in the performance. This deterioration is greater with DB3 compared to DB2.

The further CAE tests of this investigation show no dependency of *normalization* and *gray-scale reduction* on the parameters *feature size* and *rotation*.

Computational effort

The two parameters of investigation have no impact on the number or on the duration of the correlation operations.

However, reducing the gray-scale depth provide the opportunity of saving computational effort and memory with the MCU implementation. Assuming a reduction to half the range, the intensity values of two pixels can be stored in one byte. Furthermore, this enables a parallel processing of the pixel values. A parallelizable operation within the correlation is the multiplication instruction.

A parallelization involves preventing of overflows and generally optimizing the algorithm to a high degree. Such an optimization is out of the scope of this project. Nevertheless, the two parameters feature a potential to save computational effort.

Insights gained

A gray-scale normalization improves the biometric performance when using image distance functions that take absolute distances into account. It has no impact on the performance of the correlation coefficient.

The peformance can be preserved up to a gray-scale reduction to 5 bit. This can be beneficial if the algorithm is optimized for parallel processing of several pixels.

The parameters *normalization* and *gray-scale reduction* are score-decreasing types. The normalization operation per se as well as the reduction to less than 5 bit reduce the mean of the distributions.

8.3.8 INV10 - Information in the correlation map

Outline

The impact of the parameter *bestXScoresMean* on the biometric performance and the computational effort is documented below. The investigation includes one CAE test:

- *1_T59_bestXScoresMean*
- CT DB for T59

In all previous CAE tests, the highest score in the correlation map represents the matching score of the comparison. The question arises whether the biometric performance can be improved by taking into account more than one score.

The number of the scores can be configured using the parameter *bestXScoresMean*. The X highest scores form the matching score by calculation of their mean. Thus, a parameter value of one provides the same matching score as in the previous analysis.

Biometric performance

Table 8.25 shows the biometric performance for different values of the investigated parameter.

Table 8.25: INV10 - Biometric performance - parameter *bestXScoresMean*

bestXScoresMean	EER		
	euclid globalN	*normCC*	*corrCoeff*
1	30.5%	43.2%	21.1%
2	31.0%	43.9%	21.5%
4	32.0%	45.4%	22.2%
8	33.8%	47.8%	23.5%
16	36.0%	49.8%	26.2%

The following observations can be made:

- The best EER is achieved when only the highest score forms the matching score. As the number of the scores considered grows, the performance deteriorates. This is consistent for the three image distance functions.

Computational effort

The parameter has no impact on the number or on the duration of the correlation operations.

Insights gained

An improvement cannot be achieved by taking into account more than the highest score in the correlation map.

The parameter *bestXScoresMean* is a score-increasing type. The lower the number of the scores considered, the higher are the means of the distributions.

8.4 Part 3 - Reduction of the computational effort

The correlation coefficient is used throughout this part. The parameters investigated do not affect the inside of a correlation operation. Consequently, a similar impact is expected for all image distance functions.

8.4.1 INV11 - Offset step size

Outline

The impact of the parameter *offset step size* on the biometric performance and the computational effort is documented below. The investigation includes one CAE test:

- *1_T60_offsetStepSize*
- CT DB for T60

The number of correlation operations can be reduced directly by not taking into account every offset.

The CAE implementation provides a configurable offset step size, which is applied to every row of the search image. In addition, a step size of two within a column is applied in order to create a kind of checkerboard pattern. Figure 8.12 illustrates this for an offset step size of 2 and an offset step size of 4. The positions of the colored circles symbolize the considered offsets.

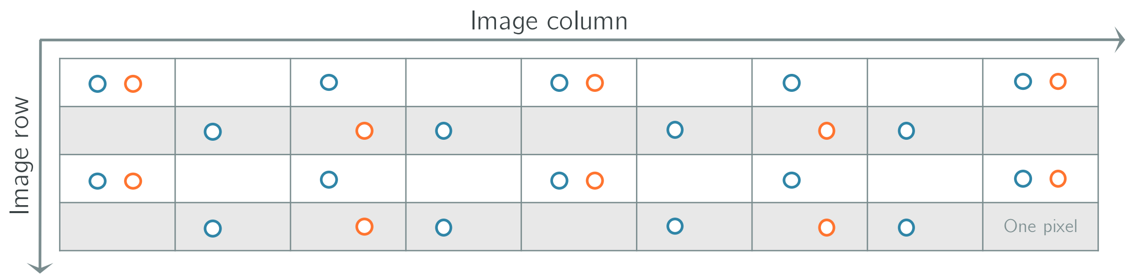

Figure 8.12: INV11 - Example of two offset step sizes

Biometric performance & computational effort

Table 8.26 shows both the biometric performance as well as the impact on the computational effort.

Table 8.26: INV11 - Impact of various offset step sizes

Offset step size	C-OP factor	EER - *corrCoeff*	
		DB2	DB3
1	1	20.2%	29.0%
2	0.50	20.7%	29.5%
4	0.25	22.0%	30.1%
6	0.17	23.4%	30.3%
8	0.13	25.3%	30.9%

The following observations can be made:

- The C-OP factor is the reciprocal of the offset step size.
- The EER deteriorates progressively with increasing step sizes. The deterioration is greater with DB2 than with DB3, especially with large step sizes.

This is the expected relation between biometric performance and computational effort when skipping alignments. The decrease in performance can be explained by the missing of actual matching scores at the offsets not taken into account.

Insights gained

The skipping of offsets provides high effort savings with an acceptable performance deterioration. For example, a step size of two almost preserves the performance and saves half the correlation operations.

The parameter *offset step size* is a score-increasing type. The lower the step size, the higher are the means of the distributions.

8.4.2 INV12 - Termination at a certain score

Outline

The parameter *earlyReturn*, which terminates the correlation at a certain score, is examined. Its impact on the biometric performance and the computational effort is documented below. The investigation includes the following CAE tests:

- *1_T61_earlyReturn_reference*
- *1_T62_earlyReturn_0.5_0.531*
- *1_T63_earlyReturn_0.6_0.631*
- *1_T64_earlyReturn_0.7_0.731*

The image distance functions create a correlation map composed of scores for every offset of every rotation step. The highest score in the map is the matching score of the comparison. The decision whether match or non-match is met after comparing the matching score with the system threshold. If the score is greater than or equal to the threshold, the decision is match.

The exact value of the matching score is not of interest. Furthermore, if one score reaches the threshold, all subsequently calculated scores of the correlation map will not change the decision. This characteristic of correlation-based matching offers a high potential for saving computational effort, but premises a known system threshold.

The CAE implementation includes a termination mechanism of the correlation process. When a certain score is reached, the comparison is finished and this current score is set as matching score.

The impact of this parameter is investigated for a configuration without considering rotation and one with considering rotation.

Biometric performance

First a reference test is carried out in order to decide on reasonable values for the parameter *earlyReturn*. Figure 8.13 shows the distribution chart of one of the reference configurations. The vertical lines indicate the matching scores that are applied as parameter values. Ideally, the termination shortens the genuine comparisons without affecting the biometric performance by shortening the impostor comparisons. In order to understand the effect, termination scores that are expected to decrease the performance are also applied.

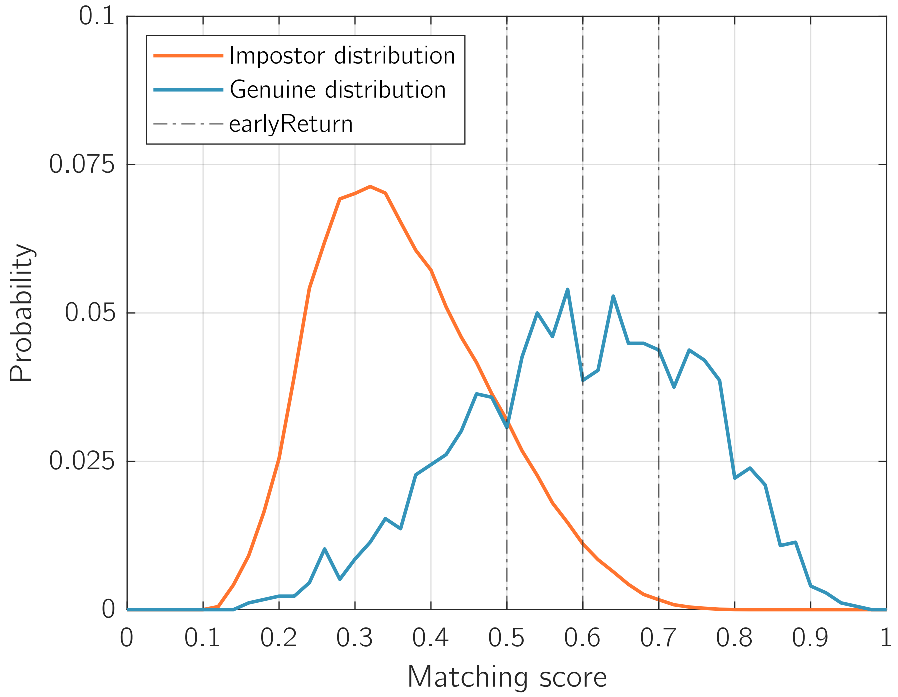

Figure 8.13: INV12 - Distribution chart of the reference configuration (w/o rotation)

For the configuration that considers rotation, similar termination scores are applied, taking into account the shift in the distributions. Table 8.27 shows the parameter values and the biometric performance for all configurations of this investigation.

Table 8.27: INV12 - Biometric performance - parameter *earlyReturn*

Rotation	*earlyReturn*	EER
noRotation	1 (no termination)	20.2%
	0.5	
	0.6	
	0.7	
(-3° ... 3°) in 1° steps	1 (no termination)	17.4%
	0.531	
	0.631	
	0.731	

The following observations can be made:

- The EER does not change for any of the termination scores applied. This holds for both types of configurations.

The DET chart in figure 8.14 shows the reason for that.

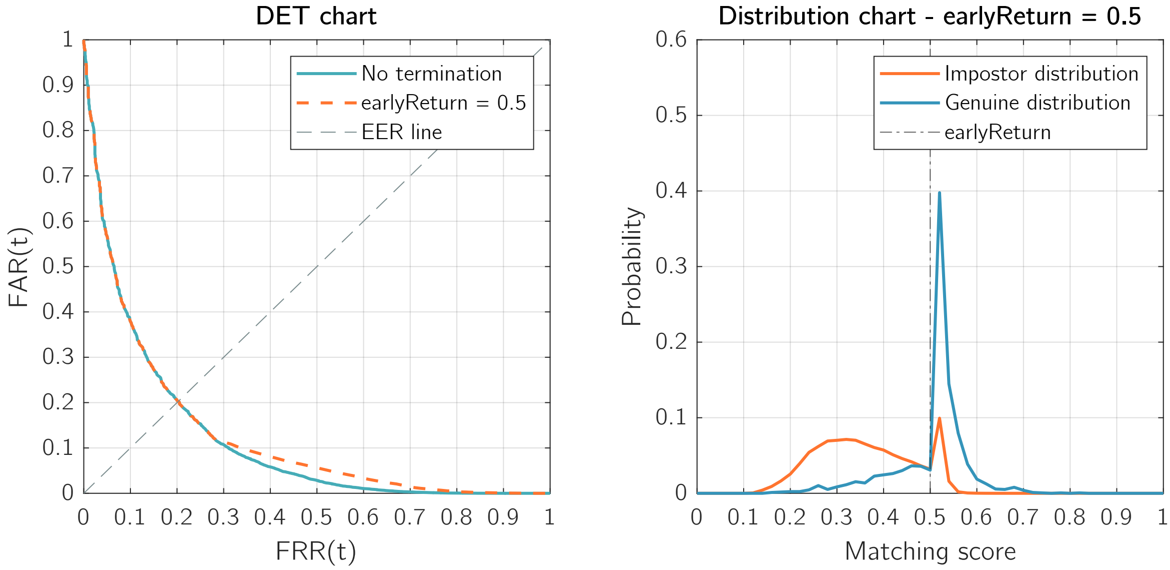

Figure 8.14: INV12 - Change in the DET and distribution chart through *earlyReturn*

The biometric performance is decreased for system thresholds higher than the applied termination score of 0.5. The EER corresponds to a lower system threshold and is therefore not affected. The deterioration in performance can be explained with the distribution chart of the figure above. Terminating the correlation process increases the probability for scores slightly higher than the termination score. This extends the overlapping areas between the distributions when these scores are used as a system threshold. Thus, the corresponding error rates FAR and FRR are increased for these operating points.

For higher termination scores, the change in the DET charts decreases. With a termination score of 0.7, a deterioration is no longer discernible in the DET chart.

Computational effort

Table 8.28 summarizes the outcomes concerning the computational effort.

Table 8.28: INV12 - Computational effort - parameter *earlyReturn*

Rotation	*earlyReturn*	C-OP factor	
		Genuine comparisons	Impostor comparisons
noRotation	1 (no termination)	1	1
	0.5	0.588	0.926
	0.6	0.736	0.984
	0.7	0.857	0.999
(-3° ... +3°) in 1° steps	1 (no termination)	1	1
	0.531	0.320	0.898
	0.631	0.515	0.979
	0.731	0.731	0.999

The following observations can be made:

- The lower the termination score, the greater are the savings for both types of comparisons.
- As expected, the genuine comparisons are more affected than the impostor comparisons.
- The savings are greater with configurations that take rotation into account.

The last observation can be explained by the enormously increase in the correlation operations with rotation. Consequently, the savings are greater in the event of a termination.

The C-OP factor for the impostor comparisons can be used to evaluate the impact of the parameter on the biometric performance. A factor of one proves the preservation of the performance for all operating points.

Insights gained

The termination of the correlation process at a certain score provides effort savings with a performance preservation. For the test configurations in this investigation, an effort saving of nearly 15% can be achieved for genuine comparisons. When rotation is considered, this saving increases to approximately 27%.

This is expected to grow with the biometric performance. A better performance means a better separation of the distributions. Thus, the potential for reducing the number of correlation operations is higher.

The parameter *earlyReturn* cannot be categorized in the defined types because it has no direct impact on the calculation of the correlation scores.

8.5 Conclusion

In this section a conclusion is drawn for the first phase of the system requirements analysis. This comprises a summary of the investigations and a CAE test that combines all parameters in one configuration. The outcomes of that are then compared to the references outcomes of the phase.

Table 8.29 summarizes this phase. This includes the investigations, the impact of the corresponding parameters on biometric performance and computational effort as well as their type categorization. The type describes the development of the scores for the trend of the parameter value that leads to an performance improvement.

Table 8.29: Phase 1 conclusion - overview

Investigation	Impact of the parameter	Parameter type 1 – *score-increasing* 2 – *score-decreasing*
INV4 - Basic rotation	Performance improvement with enormous increase in effort	1
INV5 - Feature size	Performance improvement with increase in effort	2
INV6 - Feature shape (aspect ratio)	Performance improvement with effort savings	2
INV7 - Resolution	Performance improvement with effort savings	1
INV8 - Low-pass filtering	Performance improvement without impact on effort	1
INV9 - Normalization	No improvement (*corrCoeff*) / performance improvement (other), no impact on effort	2
INV9 - Gray-scale reduction	Potential effort savings with performance preservation	
INV10 - Information in the correlation map	No improvement, no impact on effort	1
INV11 - Offset step size	Effort savings with slight performance deterioration	1
INV12 - Termination at certain score	Effort savings with performance preservation	-

The analysis reveals a number of parameters that enable an adaption of correlation-based algorithms to the conditions of this project. As expected, an improvement in the biometric performance is usually associated with an increase in the computational effort. The parameters *resolution* and *feature shape* are exceptions, which are hereby highlighted.

One single *conlusion configuration* that combines the beneficial parameters is defined. This enables a comparison with the reference outcomes of this phase. The *reference configuration* of the first investigation is described below:

Phase 1: Reference configuration

- An enrollment template...
  - is the entire image
  - in its original state.
- A verification template...
  - is composed of one feature of a size of $32\,\text{px} \times 32\,\text{px}$
  - in its original state.
- A comparison...
  - is carried out using all image distance function,
  - taking into account every offset,
  - without considering rotation and
  - without terminating at a certain score.

The following *conclusion configuration* targets a balance between biometric performance and computational effort. An algorithm optimization is out of scope for this project. Thus, the impact of the parameters on each other is not examined. Furthermore, the selection of the parameter values describes a compromise taking into account all image distance functions. For each image distance function, two biometric tests are carried out, one with consideration of rotation and one without.

Phase 1: Conclusion configuration

- An enrollment template...
  - is the entire image,
  - filtered by a Gaussian filter with a size of 5,
  - scaled down by a factor of 2,
  - normalized and reduced in gray-scale depth to 4 bit.
- A verification template...
  - is composed of one feature of a size of 54 px $\times$ 24 px (aspect ratio 2.25:1),
  - filtered by a Gaussian filter with a size of 5,
  - scaled down by a factor of 2,
  - normalized and reduced in gray-scale depth to 4 bit.
- A comparison...
  - is carried out using all image distance function
  - taking into account every second offset,
  - without considering rotation / with considering rotation of $\pm 3°$ in 1° steps,
  - without terminating at a certain score[21].

[21] Due to the comparison scheme of this phase, this parameter not set. The *final configuration* of the second phase comprises an utilization of this parameter.

Table 8.30 shows the biometric performance of the configurations described above. The following table 8.31 shows the number of correlation operations. As mentioned before, the duration of a comparison as well as the needed memory is evaluated in the second phase.

Table 8.30: Phase 1 conclusion - biometric performance

Configuration	EER			
	SSD globalN	*euclid globalN*	*normCC*	*corrCoeff*
Reference	30.3%	30.3%	40.2%	22.2%
Conclusion	24.4%	24.4%	33.8%	19.7%
Conclusion w/Rotation	22.4%	22.5%	29.5%	16.9%

Table 8.31: Phase 1 conclusion - number of correlation operations

Configuration	C-OPs			
	SSD globalN	*euclid globalN*	*normCC*	*corrCoeff*
Reference	74,925			
Conclusion	8,721			
Conclusion w/Rotation	66,285			

The performance of all image distance functions is improved by the *conclusion configuration* with a saving of nearly 90% of the correlation operations. In addition, the downscaling leads to a shorter duration of a correlation operation, which reduces the computational effort even further.
The consideration of rotation leads to an improvement in the performance for all image distance functions, but results in an almost complete loss of the effort savings.

The DET charts and the distribution charts of all image distance functions are shown in appendix B.

The correlation coefficient provides the best performance. Due to its capability to handle large features, there is further optimization potential, which is exploited in the second phase of the systems requirement analysis.

9 Analysis phase 2 - Algorithm

9.1 Introduction

The second phase comprises the analysis of verification templates that are composed of several features. Figure 9.1 illustrates the comparison scheme of this phase as described in section 7.2.2. An enrollment template consists of three samples, which are the entire images. A verification template consists of several features, which are cropped from the same verification sample.

Figure 9.1: Comparison scheme of phase 2, fingerprint images are based on [Mai+02a, DB2]

The visual inspection guarantees a minimum of capture errors up to a cropping size of 144 px × 144 px. This describes the maximum size of a verification sample.

The main tests are carried out with FVC2000 DB2. The control tests are carried out with FVC2002 DB3 (CT DB) as well as with FVC2000 DB2 using a different image role pattern (CT P).

The biometric performance is evaluated based on the EER. The DET and the distribution chart of every main test can be found in an external PowerPoint file.

In this phase, the computational effort is evaluated based on the duration of a comparison and the memory required to store the enrollment and verification template. Both values are evaluated by comparing their increase or decrease in relation to a reference configuration within the investigation. The relation is described by a so-called *duration factor* as well as a so-called *memory factor*.

In order to maintain the independence of a parameter investigation, the beneficial parameters of the first phase are only applied in the conclusion of this phase.

The changes made concerning the documentation of an investigation in the interim conclusion of section 8.3.3 persist for this phase.

The entire analysis of this phase is carried out using the correlation coefficient.

9.2 Part 1 - Positioning

9.2.1 INV13 - Reference outcomes

Outline

The aim of this investigation is the creation of reference outcomes for the second phase with the two FVC databases. This includes the following CAE tests:

- *2_T65_initialTest_DB2*
- *2_T66_initialTest_DB3*

A biometric test is carried out using a single feature with a size of 36 px × 36 px.

Biometric performance

Table 9.1 shows the biometric performance of the initial configurations. Please note that all the performances documented in this chapter are based on the correlation coefficient. Hence, the image distance function is not mentioned in the tables or in the observations.

Table 9.1: INV13 - Biometric performance - references of the second phase

Database	EER
DB2	17.6%
DB3	25.8%

The following observations can be made:

- As in the first phase, a better EER can be achieved with DB2 than with DB3.

Computational effort

Table 9.2 shows the duration of a comparison and the memory required to store the enrollment and verification template.

Table 9.2: INV13 - Computational effort - references of the second phase

Database	Enrollment template size	Verification template size	Duration per comparison	Memory consumption
DB2	3 × 256px × 364px	36px × 36px	39.9s	274.26kB
DB3	3 × 300px × 300px	36px × 36px	38.6s	271.30kB

The following observations can be made:

- The duration and the memory consumption are slightly less with DB3 compared to DB2. This is due to the higher size of the DB2 images.

Insights gained

The biometric performance is better compared to the reference outcomes of the first phase. This can mainly be explained by the comparison scheme, which features an enrollment template composed of three samples instead of one. Another reason is the larger feature.

The outcomes with DB3 show the known relation to DB2. Thus, DB3 can be used for control tests in this phase.

The computational effort is much higher than the conditions defined for this project. These reference outcomes are the basis to show the development of the biometric performance and the computational effort in this phase. Thus, a comparison to the project conditions is not reasonable until the phase conclusion.

Furthermore, the outcomes appear to contradict the promising trend of the first phase. Please note that the beneficial parameters of the first phase are not applied within the investigations in this phase. Furthermore, this phase features a different comparison scheme. Consequently, a comparison of the outcomes of the two phases is not intended.

9.2.2 INV14 - Reduction of the CAE test duration

Outline

The aim of this investigation is to shorten the CAE test duration in this phase. This includes the following CAE tests:

- *2_T67_durationReduction_reference*
- *2_T68_durationReduction_corrCoeff_Mf*

The measures of the first phase, which are parallelization and the reduction of impostor comparisons, can be applied to the CAE tests of this phase.

However, the number of correlation operations is increased due to the use of several features and several enrollment samples. Despite the decreased number of comparisons, a longer CAE test duration is expected compared to the first phase.

A possibility to reduce this is the utilization of the MATLAB® function *normxcorr2*, which implements the correlation coefficient. This function calculates the cross correlation in the frequency domain in a highly optimized manner. Please be referred to the MATLAB® documentation for more information about *normxcorr2*.

The function is implemented in the CAE like the other image distance functions. The equality of the score distributions to the former implementation of the correlation coefficient is checked by the test procedure of the CAE version 1.03.

CAE test duration

Table 9.3 summarizes the outcomes of this investigation[22]. Both biometric tests are carried out parallelized and without skipping impostor comparisons.

Table 9.3: INV14 - CAE test durations

Image distance function	CAE test duration
corrCoeff	4.55h
corrCoeff_Mf	0.83h

[22]The durations are measured with an AMD Ryzen 5 1600X Six-Core Processor with 3.60 GHz together with 16.0 GB RAM on Windows 10 (64-Bit).

The following observations can be made:

- The use of *corrCoeff_Mf*, where *Mf* stands for MATLAB® function, shortens the CAE test duration by about a factor of 5.5.

Insights gained

The duration of a CAE test is shortened by using the corresponding MATLAB® implementation of the correlation coefficient.

Nevertheless, in order to measure the number of correlation operations or configure the interior of a matching score computation, the former implementation must be used.

9.2.3 INV15 - Image role pattern

Outline

The impact of the image role pattern on the biometric performance is documented below. This investigation includes a CAE test for each of the nine pattern presets:

- *2_T69_imageRolePattern_random1 ...*
  2_T77_imageRolePattern_random9

Biometric performance

Table 9.4 on the next page shows the biometric performance for each pattern preset.

Table 9.4: INV15 - Biometric performance with different image role patterns

Image role pattern	EER
FVC_DB2_880_3e(1eT)5v_random1	8.55%
FVC_DB2_880_3e(1eT)5v_random2	8.36%
FVC_DB2_880_3e(1eT)5v_random3	8.55%
FVC_DB2_880_3e(1eT)5v_random4	9.27%
FVC_DB2_880_3e(1eT)5v_random5	10.0%
FVC_DB2_880_3e(1eT)5v_random6	8.00%
FVC_DB2_880_3e(1eT)5v_random7	9.09%
FVC_DB2_880_3e(1eT)5v_random8	9.27%
FVC_DB2_880_3e(1eT)5v_random9	9.45%

The following observations can be made:

- The best EER can be achieved with *FVC_DB2_880_3e(1eT)5v_random6*.
- The worst EER can be achieved with *FVC_DB2_880_3e(1eT)5v_random5*.

Computational effort

The image role pattern has no impact on the duration or on the memory consumption.

Insights gained

The image role pattern has a minor impact on the biometric performance. The impact is higher than that of the patterns in the first phase. This can be explained by the visual inspection. Due to the complexity of the comparison scheme in this phase, the inspection ensures the best compromise for some volunteers. Nevertheless, the visual inspection for this phase can also be rated as successful.

The sixth pattern is used in the further analysis of this phase. The fifth one is used as control test pattern.

9.3 Part 2 - Optimization of the biometric performance

9.3.1 INV16 - Feature count

Outline

The impact of the feature count on the biometric performance and the computational effort is documented below. The investigation includes the following CAE tests:

- *2_T78_featureCount_108_xof4*
- *2_T78a_featureCount_108_xof4_reverseFeatureOrder*
- *2_T79_featureCount_108_xof9*
- CT P & CT DB for T78 & T79

As opposed to the first phase, several features are used in this phase. The verification sample is divided into sub-images of equal size that form the verification template. With regard to the division, two cases are examined. In the first one, the sample is divided into nine features. In the second one, the sample is divided into four features. The position of the features within the sample is illustrated in figure 9.2 for both cases.

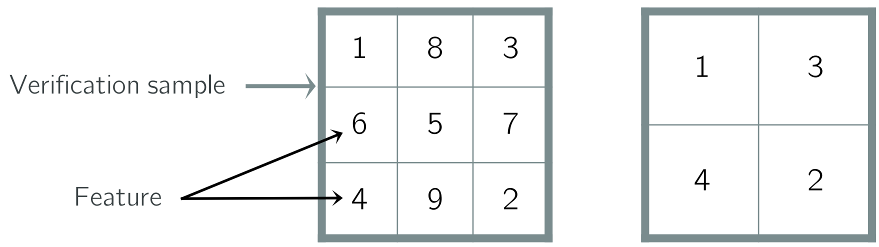

Figure 9.2: INV16 - Feature position

The feature count is distinguished as follows:

- 1 of 9: The template is composed of the feature in position 1.
- 2 of 9: The template is composed of the features in position 1 and 2.
- 3 of 9: The template is composed of the features in position 1, 2 and 3.
- 4 of 9: ...

Thus, the feature count involves fix feature positions. For one verification sample, the first feature is the same for each feature count applied. This is implemented in the same manner for the division into four features.

The investigation of the parameter *feature count* is carried out based on a sensor size of 108 px × 108 px, which corresponds to the size of the verification sample. The feature size results from the division case. Figure 9.3 illustrates this with the example of a *feature count* of *2 of 9*.

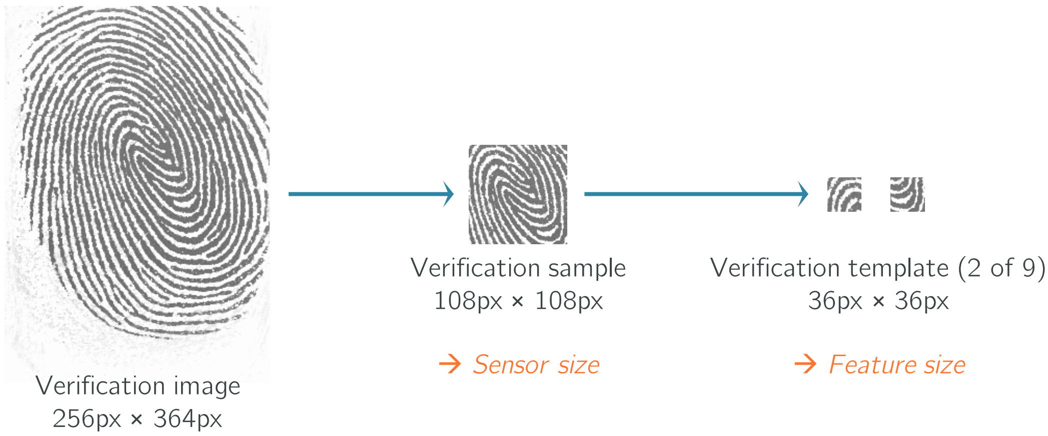

Figure 9.3: INV16 - Phase 2 scenario, fingerprint images are based on [Mai+02a, DB2]

The variation of *sensor size* and *feature size* is the main part of the analysis in the this phase. In the following, these two parameters define a so-called *phase 2 scenario*.

The CAE handles several parts of enrollment template and verification template within the comparison as follows. The highest score of one feature is found in the correlation maps of all parts of the enrollment template. All feature scores are then combined into one matching score by calculating their mean.

Biometric performance

Table 9.5 shows the biometric performance for various number of features when the sample is divided into nine features.

Table 9.5: INV16 - Biometric performance for various number of features (max. 9)

Phase 2 scenario	Feature count	EER	
		DB2	DB3
Sensor size: 108px × 108px Feature size: 36px × 36px	1 of 9	17.3%	25.8%
	2 of 9	13.5%	21.8%
	3 of 9	12.7%	21.8%
	4 of 9	11.5%	21.1%
	5 of 9	11.6%	19.8%
	6 of 9	11.8%	20.7%
	7 of 9	12.3%	20.6%
	8 of 9	12.0%	20.7%
	9 of 9	11.6%	20.2%

The following observations can be made:

- The greatest EER improvement is achieved using 4 features with DB2 respectively 5 features with DB3.
- For feature counts higher than that with the best performance, the EER does not develop consistently.

The last observation can be explained by the amount of information, which varies for the feature positions. A feature that captures the singularity of a delta region contains more distinctive information as a feature that captures a regular part of the ridge-valley pattern. Moreover, the weight of one feature with regard to the matching score decreases with each additional feature. Consequently, as the number of features increases, the biometric performance is expected to converge towards a certain value.

Table 9.6 on the next page shows the biometric performance for various numbers of features when the sample is divided into four features.

Table 9.6: INV16 - Biometric performance for various numbers of features (max. 4)

Phase 2 scenario	Feature count	EER		
		DB2	DB3	DB2 T78a Reverse order of feature 2 & 3
Sensor size: 108px × 108px Feature size: 54px × 54px	1 of 4	11.27%	19.27%	11.27%
	2 of 4	8.00%	15.82%	10.18%
	3 of 4	8.00%	16.36%	8.00%
	4 of 4	7.64%	15.45%	7.64%

The following observations can be made:

- The greatest EER improvement is achieved using 4 features.
- The performance is overall better compared to the previous table.
- From 2 features to 3 features, no improvement is achieved with DB2. A deterioration can be observed for that with DB3. The CAE test T78a features a reverse order of the feature positions 2 and 3. This results in a compensation of the effect.

The better performance with a division into four features can be explained by the larger size of those features. Nevertheless, the best performance can be achieved with four features for both cases of division. For the scenario in table 9.6, a higher number of features is not expected to significantly improve the performance.

The impact of the feature order on the biometric performance can be explained by the finite number of comparisons. This is expected to be compensated if a higher variance of the fingerprints can be guaranteed.

The parameter *feature count* does not affect the interior of a score computation. Therefore, a categorizing concerning its effect on the mean values is not reasonable. The matching score is averaged by taking into account more than one feature. This improves the error rates if the standard deviation of the distributions is decreased.

That effect can be observed in the distribution charts of this investigation up to four features. For a higher number of features, the standard deviation varies slightly but does not show a consistent trend. The mean values of the distributions are not significantly affected. This confirms the above explanation of the development of the EER values and their associated convergence.

Computational effort

Table 9.7 summarizes the outcomes concerning the computational effort.

Table 9.7: INV16 - Computational effort

Phase 2 scenario	Feature count	Duration factor	Memory factor
Sensor size: 108px × 108px Feature size: 36px × 36px	1 of 9	1	1
	2 of 9	2	1.005
	3 of 9	3	1.009
	4 of 9	4	1.014
	...		
Sensor size: 108px × 108px Feature size: 54px × 54px	1 of 4	1.67	1.006
	2 of 4	3.34	1.016
	3 of 4	5.01	1.027
	4 of 4	6.68	1.037

The following observations can be made:

- The duration increases proportionally with the number of features.
- For a feature count that covers the entire sensor, the duration is lower with larger features.
- The memory consumption is affected slightly by the increase of the verification template.

Insights gained

An use of several features improves the biometric performance with an increase in the computational effort. The duration of the comparison scales with the number of features, whereas the memory consumption is slightly affected.

The best performance can be achieved with four features. However, two features are reasonable in terms of the duration of a comparison.

Moreover, a higher feature size is generally beneficial for the biometric performance and the duration.

The effect of the parameter *feature count* can be described as a *score-averaging type*.

9.3.2 INV17 - Sensor size

Outline

The impact of the sensor size on the biometric performance and the computational effort is documented below. The investigation includes the following CAE tests:

- *2_T80_sensorSize_96*
- *2_T81_sensorSize_108*
- *2_T82_sensorSize_120*
- *2_T83_sensorSize_132*
- *2_T84_sensorSize_144*
- CT P for each CAE test

This investigation aims at the question of a sufficient sensor size. A CAE test is carried out for each of the following sizes. The areas relate to a sensor resolution of 500 dpi.

- 96 px $\times$ 96 px - 23.78 mm^2
- 108 px $\times$ 108 px - 30.10 mm^2
- 120 px $\times$ 120 px - 37.16 mm^2
- 132 px $\times$ 132 px - 44.97 mm^2
- 144 px $\times$ 144 px - 53.51 mm^2

In order to make a comparison of the outcomes possible, four features that cover the entire sensor area are used. Consequently, the feature size differs for the different sensor sizes.

Biometric performance

Table 9.8 summarizes the outcomes concerning the biometric performance.

Table 9.8: INV17 - Biometric performance for various sensor sizes

Phase 2 scenario Sensor size / Feature size	Feature count	EER
96px × 96px / 48px × 48px	4 of 4	8.54%
108px × 108px / 54px × 54px		7.64%
120px × 120px / 60px × 60px		6.18%
132px × 132px / 66px × 66px		5.46%
144px × 144px / 72px × 72px		4.18%

The following observations can be made:

- The EER is improved with larger sensor sizes.
- The improvement can be described as continous if the effect of the finite number of comparisons is taken into account.

The score-averaging effect of the parameter *feature count* is expected to be similar for the different sensor sizes investigated. Consequently, the improvement in the biometric performance can be explained by the increase in the feature size.

Computational effort

Table 9.9 on the next page summarizes the outcomes concerning the computational effort.

Table 9.9: INV17 - Computational effort for various sensor sizes

Phase 2 scenario Sensor size / Feature size	Feature count	Duration factor	Memory factor
96px × 96px / 48px × 48px	4 of 4	1	1
108px × 108px / 54px × 54px		1.16	1.01
120px × 120px / 60px × 60px		1.33	1.02
132px × 132px / 66px × 66px		1.36	1.03
144px × 144px / 72px × 72px		1.67	1.04

The following observations can be made:

- The duration of a comparison is higher with larger sensors.
- The memory consumption is affected slightly by the increase of the verification template.
- The gray-marked duration factor at a feature size of 66 px × 66 px is due to unexpected optimization behavior of the compiler of the MCU IDE. For reasons of time, the cause is not investigated further in this project.

The duration factor describes the exact relation as observed with the feature size in figure 8.7. This can be explained by the proportional increase in the duration with the number of features.

Insights gained

The impact of the different sensor sizes corresponds to that of the parameter *feature size*. The question of a sufficient sensor size can therefore be answered by the best combination of feature size and feature count.

Due to the size of the enrollment template, the memory consumption is slightly affected.

The parameter *sensor size* is a score-decreasing type. The larger the sensor, the lower are the means of the distributions.

9.4 Part 3 - Reduction of the computational effort

9.4.1 INV18 - Enrollment sample count

Outline

The impact of the enrollment template size on the biometric performance and the computational effort is documented below. The investigation includes the following CAE tests:

- *2_T85_sampleMerge_108_3*
- *2_T86_sampleMerge_108_2*
- *2_T87_sampleMerge_108_1*
- CT DB & CT P for each CAE test

For the comparison scheme of this phase, three out of eight samples per volunteer are used to create the enrollment template. A reduction of this count is investigated. In order to keep the outcomes comparable, unused enrollment samples are not used for verification.

Biometric performance

Table 9.10 summarizes the outcomes concerning the biometric performance.

Table 9.10: INV18 - Biometric performance for various enrollment sample counts

Phase 2 scenario	Enrollment sample count	EER	
		DB2	DB3
Sensor size: 108px × 108px	3	8.00%	15.82%
Feature size: 54px × 54px	2	9.82%	18.00%
Feature count: 2 of 4	1	12.36%	26.73%

The following observations can be made:

- The EER is deteriorated with a lower enrollment sample count.
- The deterioration is greater with DB3 compared to DB2.

Computational effort

Table 9.11 summarizes the outcomes concerning the computational effort.

Table 9.11: INV18 - Computational effort for various enrollment sample counts

Phase 2 scenario	Enrollment sample count	Duration factor	Memory factor
Sensor size: 108px × 108px Feature size: 54px × 54px Feature count: 2 of 4	3	1	1
	2	0.67	0.67
	1	0.33	0.35

The following observations can be made:

- The duration and memory consumption are affected in a similar way.
- The duration increases proportionally with the number of enrollment samples.
- The memory consumption increases nearly proportionally with the number of enrollment samples. This is due to the memory consumption of the verification template.

Insights gained

A reduction of the number of samples in the enrollment template provides high effort savings, but decreases the biometric performance.

The parameter *enrollment sample count* is a score-increasing type. The higher the number of samples in the template, the higher are the means of the distributions.

9.5 Conclusion

In this section a conclusion is drawn for the second phase of the system requirements analysis. A summary of the investigations is followed by a comparison of the reference and the CAE test with the best performance achieved. Finally, the concluding configuration of the system requirements analysis is described, which combines the insights of both phases.

Table 9.12 summarizes this phase. This includes the investigations, the impact of the corresponding parameters on biometric performance and computational effort as well as their type categorization. The type describes the development of the scores for the trend of the parameter value that leads to a performance improvement.

Table 9.12: Phase 2 conclusion - overview

Investigation	Impact of the parameter	Parameter type 1 – *score-increasing* 2 – *score-decreasing* 3 – *score-averaging*
INV16 - Feature count	Performance improvement with enormous increase in duration and minor increase in memory consumption	3
INV17 - Sensor size	Performance improvement with increase in duration and minor increase in memory consumption	2
INV18 - Enrollment sample count	Effort savings (duration & memory cons.) with performance decrease	1

The investigations in this phase are focused on the amount of information, represented by the size of enrollment and verification template. An improvement in the biometric performance is invariably associated with an increase in the computational effort.

Table 9.13 shows the outcomes of the reference configuration and the configuration with the best biometric performance achieved.
The enrollment template consists of three enrollment samples for both configurations. The *phase 2 scenarios* in the table represent the two extrema concerning the size of the verification template. Moreover, no pre-processing is applied to the templates and the biometric tests are carried out using the correlation coefficient.

Table 9.13: Phase 2 conclusion - impact the of amount of information

Configuration	Phase 2 scenario	EER	Duration factor	Memory factor
Reference	Sensor size: 108px × 108px Feature size: 36px × 36px Feature count: 1 of 9	17.6%	1	1
INV17 - T84	Sensor size: 144px × 144px Feature size: 72px × 72px Feature count: 4 of 4	4.18%	9.62	1.07

The biometric performance represented by the EER is improved to 4.18%. This corresponds to 23 false rejections out of 550 genuine comparisons. However, the computational effort of a verification process is far beyond the conditions of this project, even without considering any rotation. The duration with the second configuration is approximately 384 s. The memory required is approximately 293 kB. The question arises of a reasonable amount of information in in relation to the restricted computational power.

The main conditions concerning the correlation-based algorithm and the associated verification system in this project are mentioned again below:

- Sensor area range: 25 mm^2 to 50 mm^2
- Maximum duration of a verification process: 1 s at 96 MHz
- Available memory on the MCU: 32 kB

The analysis of the second phase reveals two features as an optimal number. With a feature size of 72 px $\times$ 72 px, this corresponds to an area of 26.76 mm^2. In addition, duration and memory can be reduced by using two enrollment samples instead of three. In addition, the analysis of the first phase reveals a number of parameters that have a beneficial impact concerning the above conditions.

The following configuration combines the insights of both phases into a *final configuration*, which targets the conditions of this project. However, the configuration describes a compromise between biometric performance and computational effort.

Phase 2: Final configuration

- An enrollment template...
  - consists of two samples,
  - filtered by a Gaussian filter with a size of 5,
  - scaled down by a factor of 2,
  - normalized and reduced in gray-scale depth to 4 bit.
- A verification template...
  - is composed of two features of a size of 108 px × 48 px (aspect ratio 2.25:1), which corresponds to an area of 26.76 mm^2,
  - filtered by a Gaussian filter with a size of 5,
  - scaled down by a factor of 2,
  - normalized and reduced in gray-scale depth to 4 bit.
- A comparison...
  - is carried out using the correlation coefficient,
  - taking into account every second offset,
  - without considering rotation,
  - with terminating the comparison at a score of 0.57 or higher.

The enrollment template and the verification template are scaled down by a factor of two. Thus, the effective size of a feature is 54 px × 24 px. With regard to the duration of one correlation operation, this corresponds to a feature of 36 px × 36 px.

Table 9.14 on the next page shows the biometric performance and the computational effort when using this configuration.

Table 9.14: Phase 2 conclusion - outcomes of the *final configuration*

EER	Duration		Memory consumption
	Genuine comparison	Impostor comparison	
6.55%	1.97s	4.35s	48.03kB

The DET and the distribution chart of this configuration are shown in appendix C.

In the following, the biometric performance and the computational effort of the *final configuration* are evaluated with regard to their accuracy and compared with the conditions of this project. A statement as to whether correlation-based matching is convenient in the target use case can be found in the project conclusion in chapter 10.

Biometric performance

The EER in the table above corresponds to the following number of errors:

- 36 false rejections out of 550 genuine comparisons
- 3,902 false acceptances out of 59,590 impostor comparisons

This consequences in the following error rates and related error bands concerning the »Rule of 30«[23]:

- $FRR_{true} = FRR_{obs} \pm 30\,\% = [4.585\,\%, 8.515\,\%]$
- $FAR_{true} = FAR_{obs} \pm 10\,\% = [5.895\,\%, 7.205\,\%]$

These are the error rates for the system operating point that is based on the corresponding threshold of the EER. Further operating points are documented in appendix C.

The number of false rejections is slightly higher than the required 30 errors for an error band of 30%. A further analysis based on the EER is therefore not recommended. In order to achieve a balance between the number of false rejections and the number of false acceptances, an operating point with a lower threshold can be used. However, a further optimization in terms of the entire system performance requires an adapted comparison scheme or a bigger database.

[23]With a minimum number of 260 errors, one can be 90% confident that the true error is within a 10% error band of the observed value. This is applied to FAR_{obs}.

With regard to the use cases mentioned in the introduction and the described boundaries of the database, the biometric performance achieved with the *final configuration* can be rated as a sufficiently reliable. The verification template corresponds to an area of 26.76 mm^2. Consequently, a sensor of a size of 108 px × 108 px, which corresponds to an area of 30.1 mm^2, is adequate.

Duration of a verification process

The average duration of a genuine comparison is used as the final value. Due to the *specific positive claim* in this project, the duration of an impostor comparison is of decreased interest.

As described in section 7.3, the duration of a comparison is an approximation of the duration of a verification process. The following equation relates both durations while taking the applied parameters into account:

$$t_{Verification} = t_{Comparison} \cdot x_C + t_{vT} \tag{9.1}$$

with t_{vT}: Time for creating the verification template
x_C: Time factor for optimizing the correlation process

The preparation of the verification template in general as well as the implementation of the following parameters are assigned to t_{vT}:

- *Feature size*
- *Feature shape*
- *Feature count*
- *Low-pass filtering*
- *Resolution*
- *Normalization*
- *Gray-scale reduction*

The analysis reveals the potential of the parameters to reduce the duration of a comparison. At the same time, the parameters increase the time required to create the template. With respect to the *final configuration*, this time can no longer be considered negligible.

The implementations of the parameters *offset step size* and *earlyReturn* are assigned to x_C. They have to be applied to the interior of the image distance function. Thus, their impact on the duration can be seen as a factor that increases the duration of a correlation operation.

In summary, the duration of a verification process is higher than the measured duration. However, the duration of a comparison is expected to be the bulk of the verification process. The *final configuration* features a measured duration of 1.97 s, which is nearly twice the value of the target.

Memory consumption

The memory consumption of the templates is higher than 48 kB. This is about 150% of the available memory on the MCU. The real memory consumption is higher due to the memory required for the implementation of the parameters and the image distance function. However, this is expected to be insignificantly compared to the memory required to store the templates.

10 Conclusion

The system requirements analysis reveals various parameters that enable an adaption of the correlation-based matching algorithm to the project conditions. High adaptability is a characteristic of correlation-based matching. The search for the best alignment describes a tradeoff between biometric performance and computational effort. The rich amount of information in the gray-scale values can be utilized to different extents. Thus, the accuracy of the recognition can be adjusted with the effort made.

The *final configuration* of the algorithm represents a combination of the beneficial parameters using the correlation coefficient. A reliable recognition is achieved with this configuration. The related computational effort is in the same order of magnitude as the defined conditions, but exceeds their maxima. However, a potential for further improvement is expected for all parameters.

In order to give an example for the optimization potential, the *final configuration* is compared to the one that features the best performance in the analysis. This configuration utilizes the maximum sensor size to be analyzed.
The biometric performance is nearly preserved with the *final configuration*. The verification process is about 200 times faster and features a memory consumption of about 16%. Especially the downscaling operation is herewith highlighted. A reduction of the resolution leads to a perfomance improvement with enormous effort savings. Therefore, correlation-based matching is expected to be also appropriate with low-resolution sensors.

The analysis reveals that an increase in the amount of information does not automatically mean an improvement in the performance. Beyond a certain point, only the effort is increased. The feature size and the feature count applied in the *final configuration* represent a good balance. Consequently, the amount of information in the smallest sensor size analyzed, which is $25\,\mathrm{mm}^2$, is evaluated to be sufficient for fingerprint recognition. However, a larger sensor offers the possibility of selecting the features with regard to their quality and distinctiveness.

The correlation coefficient is successfully implemented on the target hardware architecture. The regularity of the correlation offers various possibilities for optimizing the implementation.

In summary, the system requirements analysis proves the suitability of correlation-based matching for usage with limited information of partial fingerprints in an embedded environment with restricted computational power. The defined conditions are expected to be achievable. An optimization beyond that is assessed as possible.
With a mature correlation-based matching algorithm, a fingerprint-based configuration assignment in a shared car can therefore be a convenient and sufficiently secure solution.

In addition, correlation-based matching can be realized in the sense of an approximation procedure. The search for the best alignment can be implemented by a variable step size of offset and rotation. Increasing the maximum duration therefore results in a higher matching score. Thus, the system operating point can also be adjusted using the maximum duration of a verification process. This offers a higher flexibility concerning the specific use case of the application.

11 Outlook

The extensibility of the analysis environment enables a continuation of this project in terms of a more specialized analysis up to an algorithm optimization. A list of interesting issues to analyze is given in the following:

- Selection of the features concerning their information quality and distinctiveness
- Utilization of the position of the matching score
- Forming of the matching score with several features
- Expansion of the parameter *offset step size* in synergy with *earlyReturn*, furthermore consideration of rotation for a limited number of offsets
- Composition of the enrollment template with sensor-sized enrollment samples

Moreover, a combined approach that correlates the regions surround minutiae offers several advantages. Due to the knowlege of the positions of the corresponding minutiae, the number of correlation operations can be limited. In addition, these regions provide a certain distinctiveness.

With regard to the MCU implementation, the following optimization measures are assessed as promising:

- Reduction of the gray-scale depth and associated parallelization of the computations on the pixel intensity values
- Analysis of the interior of one correlation operation
  - Termination when a certain score can no longer be achieved
  - Reduction of the accuracy of the computation

The principle of measuring the smallest unit on the MCU and scaling it with information measured in the CAE can be expanded to a building-block principle. For example, the parameters *low-pass-filtering* or *normalization* can be broken down to a pixel operation. Thus, the accuracy of the duration measurement can be increased. The computational effort of an enrollment process can be analyzed in the same way.

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A Electronic appendix

The contents of the CD attached to this thesis are outlined in the following:

- Folder 1_Thesis - Contains the thesis as .pdf file
- Folder 2_ElectronicAppendix
  - Folder CAEv1.03
    - Contains the sources of the CAE in version 1.03 and the presets of the image role patterns
  - Folder FVC
    - Contains the FVC databases and the related SQLite databases provided by the hosting company as well as the changed one for DB2 after the visual inspection
  - Folder MCU_Measurement
    - Contains the C-sources of the MCU implementation
  - Folder mksqlite-2.7-win64
    - Contains the SQLite interface mksqlite in version 2.7
  - File CAE_outcomes.db - *outcome database* of the project
  - File CAE_SQLiteTableDefinitions.xlsx - CAE parameter documentation
  - File CAE_TestProcedure.xlsx - CAE testing documentation
  - File CAEv0.9_Architecture.pptx - CAE architecture - module level
  - File MCU_Measurement.xlsx - Measurement of C-OP duration
  - File Research.pptx - Comparison promising papers
  - File SRA_testDocumentationCAE.pptx - Analysis docu of CAE tests

The CD attached is available from Prof. Dr. Heike Neumann and Thomas Suwald (NXP Semiconductors Germany GmbH).

B Phase 1 - Development of the biometric performance

The DET charts and the distribution charts of the configurations described in section 8.5 are shown on the following pages. Each image distance function fills a single page.

For reasons of clarity, only the graphs of the *reference configuration* and the *conclusion configuration* with considering rotation are illustrated together per chart.

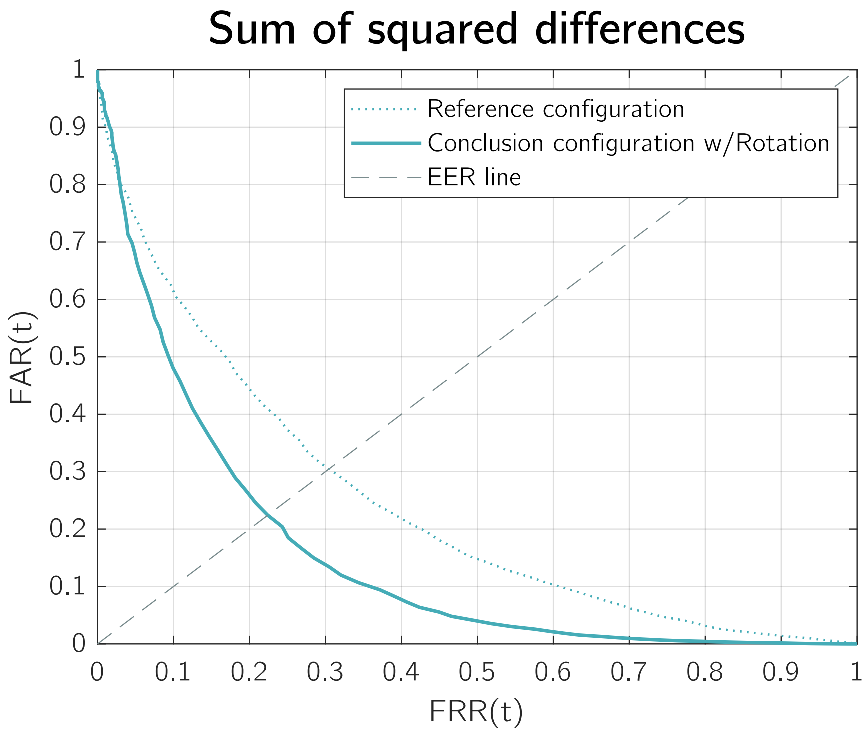

Figure B.1: Phase 1 - Development of the DET chart - *SSD globalN*

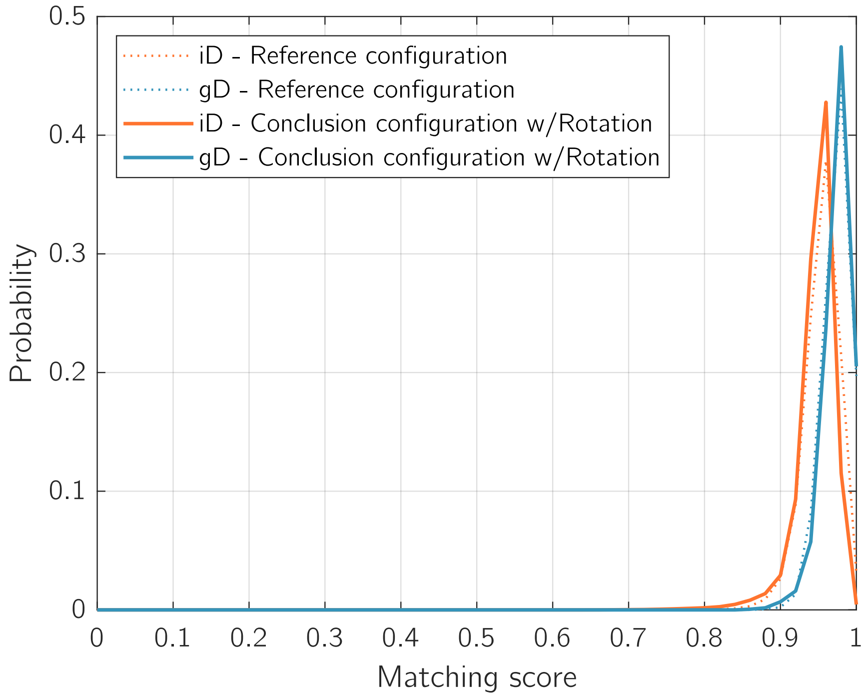

Figure B.2: Phase 1 - Development of the distribution chart - *SSD globalN*

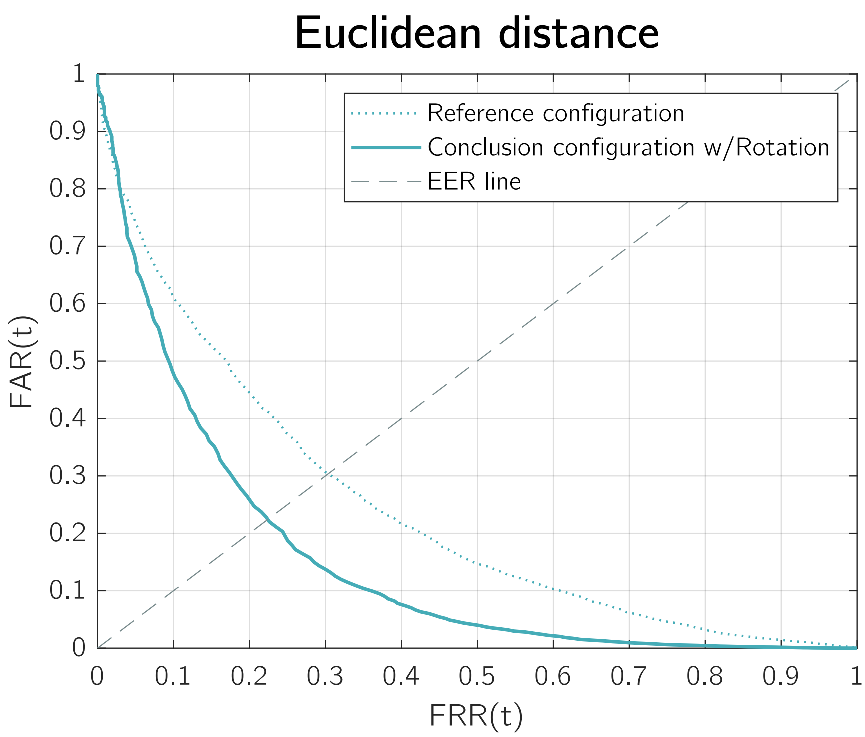

Figure B.3: Phase 1 - Development of the DET chart - *euclid globalN*

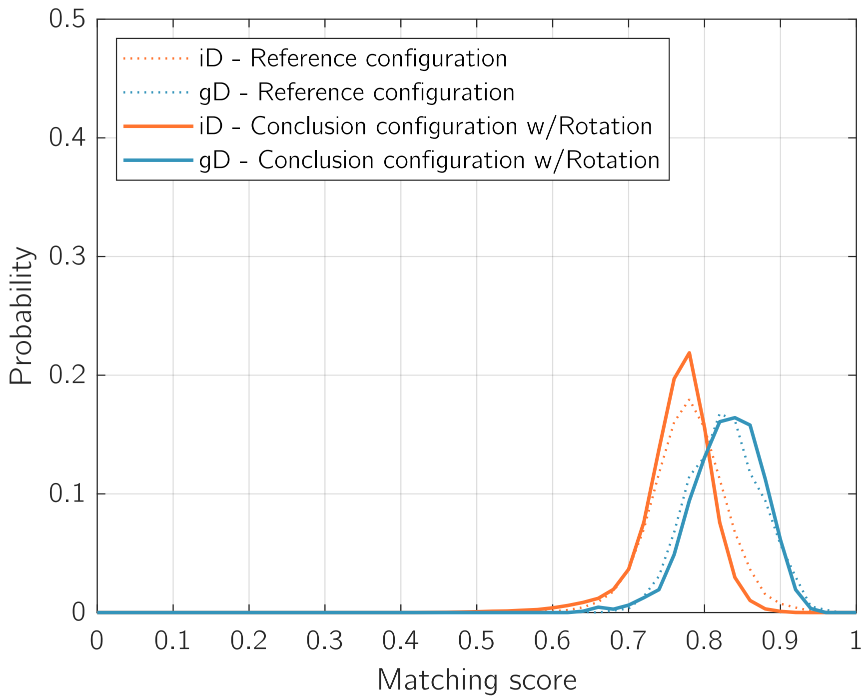

Figure B.4: Phase 1 - Development of the distribution chart - *euclid globalN*

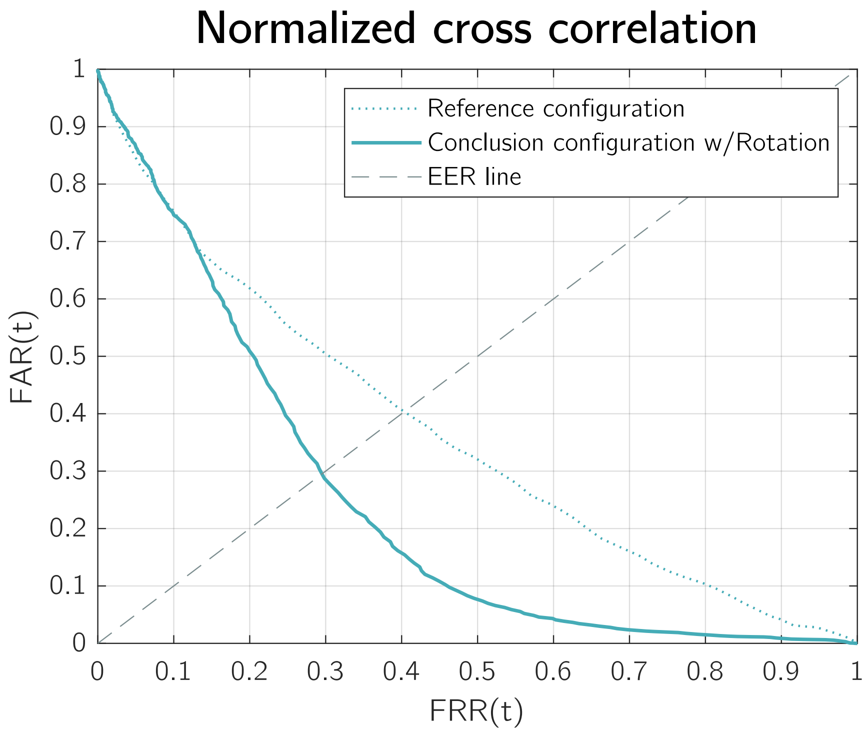

Figure B.5: Phase 1 - Development of the DET chart - *normCC*

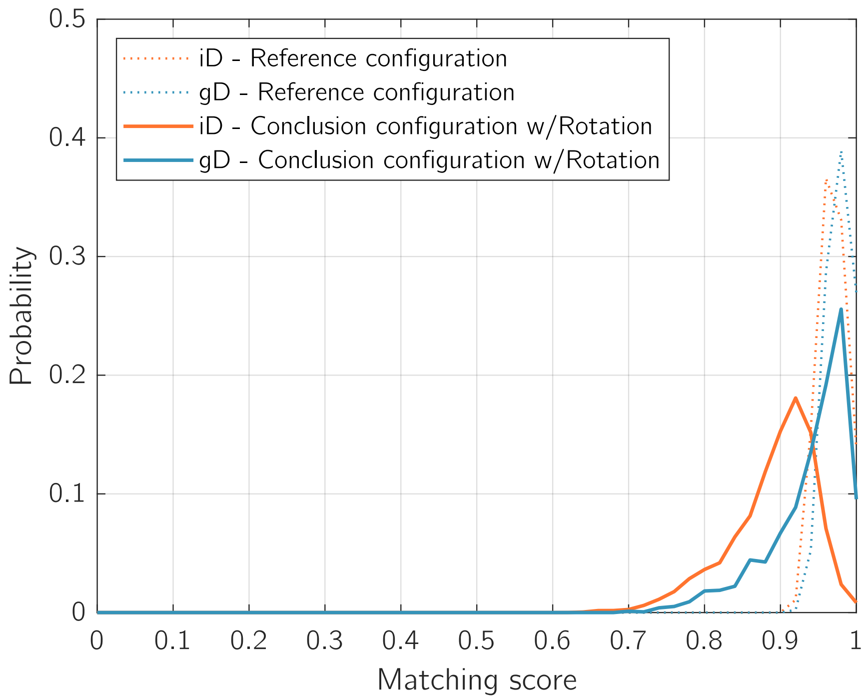

Figure B.6: Phase 1 - Development of the distribution chart - *normCC*

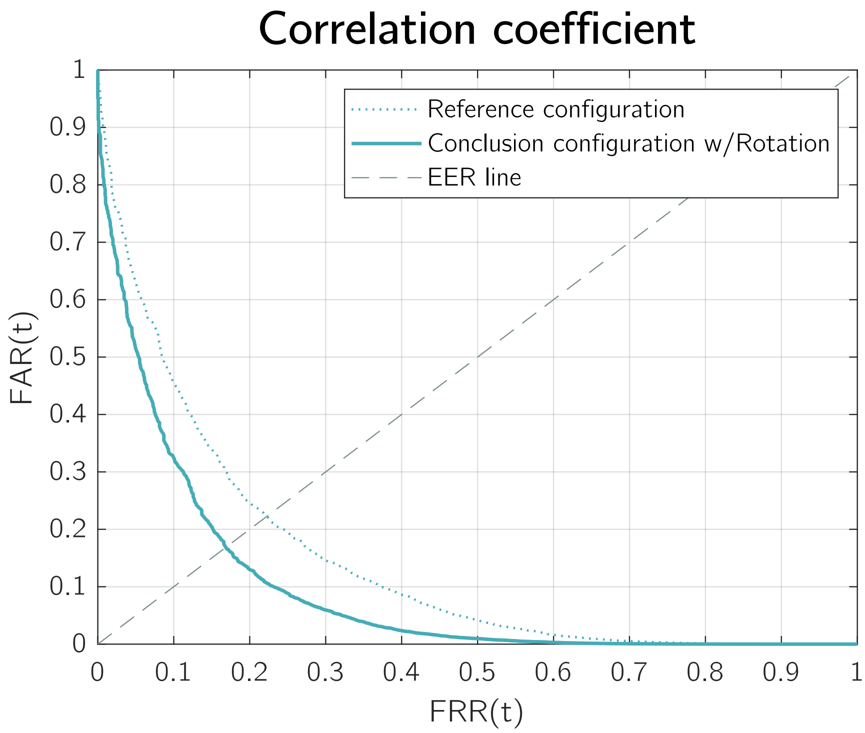

Figure B.7: Phase 1 - Development of the DET chart - *corrCoeff*

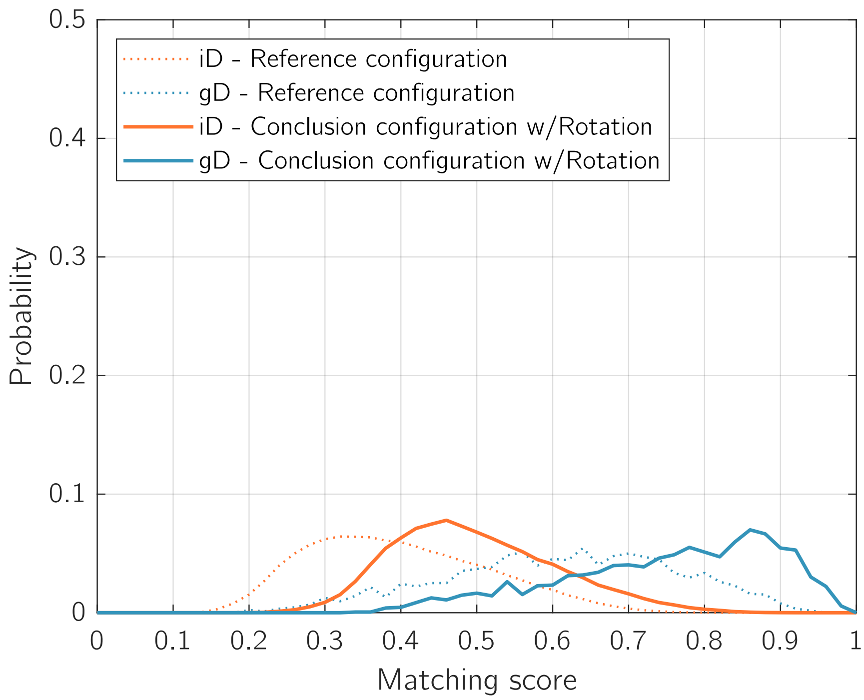

Figure B.8: Phase 1 - Development of the distribution chart - *corrCoeff*

C Phase 2 - Final biometric test

The DET chart of the *final configuration*, which is described in section 9.5, is shown below together with the detailed performance of various operating points in Table C.1.

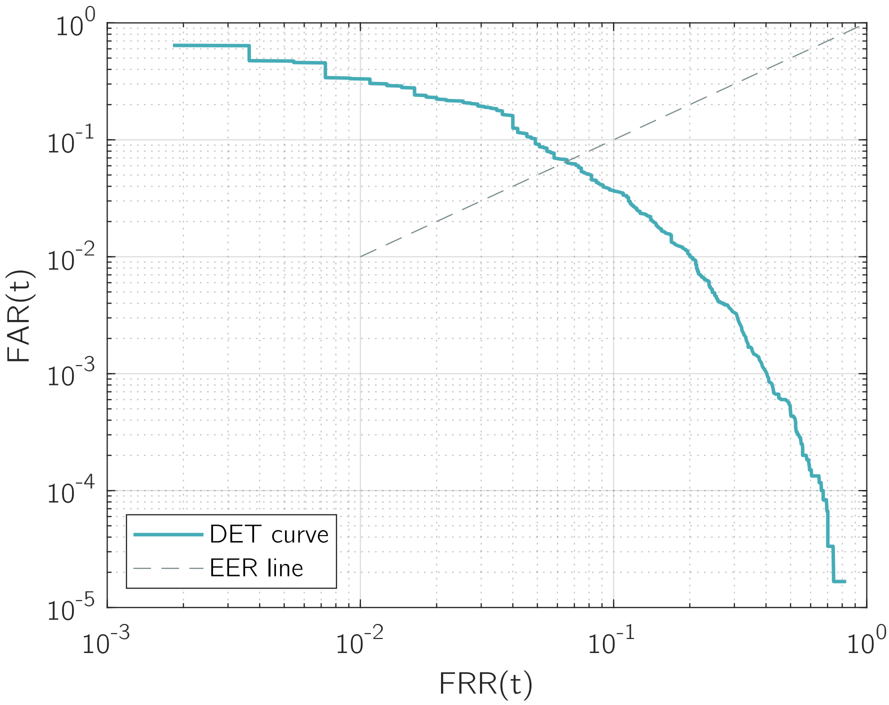

Figure C.1: Phase 2 - Final biometric test - DET chart - *corrCoeff*

Table C.1: Phase 2 - Various operating points of the *final configuration*

	FRR ~1/100	FAR ~1/10	EER	FRR 1/10	FAR 1/100	FAR 1/1000
FRR	1.09%	4.91%	6.55%	10.0%	20.2%	40.2%
FAR	33.7%	9.98%	6.55%	3.67%	1.00%	0.10%
System threshold	0.309	0.366	0.385	0.410	0.468	0.585

Figure C.2 shows the distribution chart of the *final configuration*. The vertical lines indicate some of the operating points given in table C.1. Please note that a termination score of 0.57 is applied in this configuration.

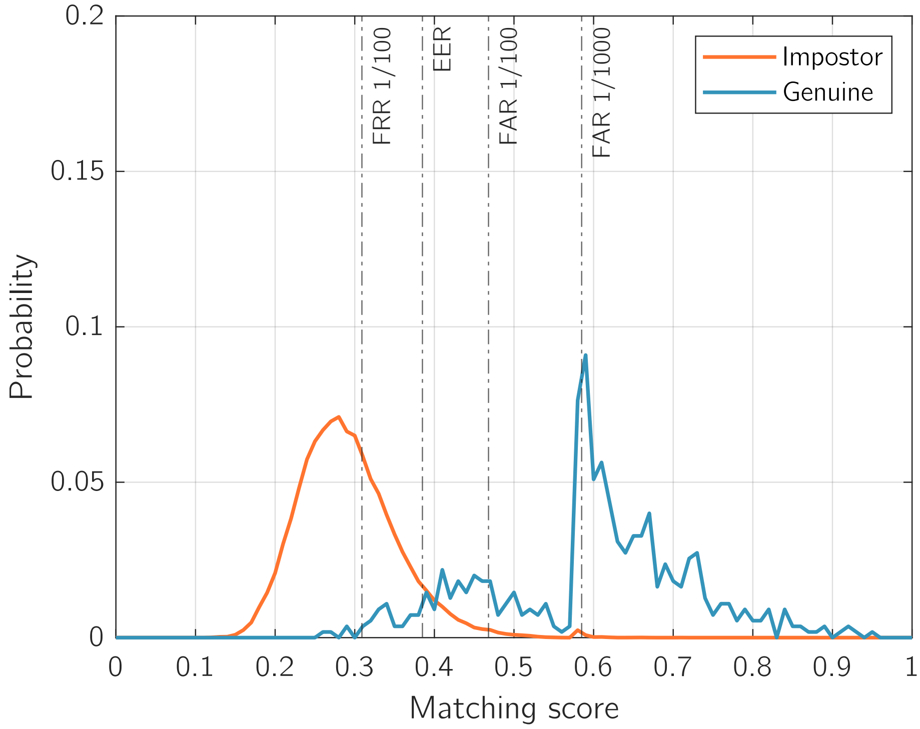

Figure C.2: Phase 2 - Final biometric test - Distribution chart - *corrCoeff*

D FVC database collection

The following information of the database collection process is quoted verbatim from the indicated sources.

FVC2000, DB2, [Mai+02a]

»

- *The fingerprints are mainly from 20 to 30 year-old students (about 50 percent male)*
- *Up to four fingers were collected for each volunteer (forefinger and middle finger of both the hands).*
- *The images were taken from untrained people in two different sessions and no efforts were made to assure a minimum acquisition quality.*
- *All the images from the same individual were acquired by interleaving the acquisition of the different fingers (e.g., first sample of left forefinger, first sample of right forefinger, first sample of left middle, first sample of right middle, second sample of the left forefinger, ...).*
- *The presence of the fingerprint cores and deltas is not guaranteed since no attention was paid on checking the correct finger position on the sensor.*
- *The sensor platens were not systematically cleaned (as usually suggested by the vendors).*
- *The acquired fingerprints were manually analyzed to assure that the maximum rotation is approximately in the range [-15°,+15°] and that each pair of impressions of the same finger has a nonnull overlapping area.*

«

FVC2002, DB3, [Mai+02b]

»

- *A total of ninety students (20 years old on the average) enrolled in the first two years of the Computer Science degree program at the University of Bologna kindly agreed to act as volunteers for providing fingerprints:*
    - *volunteers were randomly partitioned into three groups(30 persons each); each group was associated to a DB and therefore to a different fingerprint scanner;*
    - *each volunteer was invited to present him/herself at the collection place in three distinct sessions, with at least two weeks time separating each session;*
    - *forefinger and middle finger of both the hands (four fingers total) of each volunteer were acquired by interleaving the acquisition of the different fingers to maximize differences in finger placement;*
    - *no efforts were made to control image quality and the sensor platens were not systematically cleaned;*
    - *at each session, four impressions were acquired of each of the four fingers of each volunteer;*
    - *during the second session, individuals were requested to exaggerate displacement (impressions 1 and 2) and rotation (3 and 4) of the finger, not to exceed 35 degrees;*
    - *during the third session, fingers were alternatively dried (impressions 1 and 2) and moistened (3 and 4).*

In FVC2002 the data collection was carried by two final-year students, completing their Laurea thesis at BioLab.

At the end of the data collection, we had collected foreach database a total of 120 fingers and 12 impressions per finger (1440 impressions) using 30 volunteers. The size of each database to be used in the FVC2002 test, however, is established as 110 fingers, 8 impressions per finger (880 impressions) (Fig. 2). Collecting some additional data gave us a margin in case of collection errors, and also allowed us to systematically choose from the collected impressions those to include in the test databases.

An automatic all-against-all comparison was first performed by using an internally-developed fingerprint matching algorithm, to discover possible data-collection errors. False match and false non-match errors were manually analyzed: two labeling errors were discovered and removed. Fingerprints in each database were then sorted by quality *according to a quality index [9]. The top-ten quality fingers were removed from each database since they do not constitute an interesting case study. The remaining 110 fingers were split into set A (100 fingers -evaluation set) and set B (10 fingers - training set). To make set B representative of the whole database, the 110 collected fingers were ordered by quality, then the 8 images from every tenth finger were included in set B. The remaining fingers constituted set A.*

After training sets B were made available to the participants, some of them informed us of the presence of fingerprint pairs whose relative rotation exceeded the maximum specification of about 35 degrees. We were not much surprised by this, since although the persons in charge of data collection were informed of the constraint, the requirement of "exaggerating rotation but remaining within a maximum of about 35 degrees between any two samples" is not simple to implement in practice, especially when the volunteers are untrained users. A further semiautomatic analysis was then necessary to ensure that, in the evaluation sets A, the samples were compliant with the initial specifications: maximum rotation and non-null overlap between any two impressions of the same finger. Software was developed to support us in this daunting task. All of the 12 originally collected impressions of the same fingers were displayed at the same time and the authors selected a subset of 8 impressions by point and click. Once the selection was made, the software automatically compared the selected impressions and a warning was issued in case the rotation or displacement between any two pairs exceeded the maximum allowed. Fortunately, the 12 samples at our disposal always allowed us to find a subset of 8 impressions compliant with the specification.

«

Versicherung über die Selbstständigkeit

Hiermit versichere ich, dass ich die vorliegende Arbeit im Sinne der Prüfungsordnung nach §16(5) APSO-TI-BM ohne fremde Hilfe selbstständig verfasst und nur die angegebenen Hilfsmittel benutzt habe. Wörtlich oder dem Sinn nach aus anderen Werken entnommene Stellen habe ich unter Angabe der Quellen kenntlich gemacht.

Hamburg, 17. März 2021

Ort, Datum

Unterschrift