HAND SURFACE BIOMETRICS FOR PERSONAL RECOGNITION

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Abstract

Biometric personal recognition is an active research topic which has been accompanying the increasing need for improved and higher security systems. This thesis describes a full hand recognition system, which does not require any special image acquisition equipment, and works in extremely flexible conditions. Finger surface and palmprint features are extracted using PCA, LDA and PCA-LDA, from each sample hand image and then individually processed. The modalities are fused together at score level in a final stage. A deeper analysis is given into different methodologies (e.g. distance measures, fusion rules, fusion normalization), along with the comparison of experimental results derived from the variation of system operating parameters, like for example the region-of-interest (ROI) size. The achieved results confirm that biometric fusion has a great positive impact in system performance and that this approach can be used for applications requiring high levels of security, even with small ROI sizes.

Keywords

Biometrics, personal recognition, hand surface, palmprint, finger surface, multimodal fusion.
Resumo

Uma área de pesquisa que tem vindo a acompanhar a crescente necessidade de sistemas de alta segurança é a de sistemas biométricos para reconhecimento de pessoas. Esta tese descreve um sistema de reconhecimento bastante flexível, que realiza a identificação através de imagens da mão, não sendo necessário equipamento especial para aquisição das imagens. Em particular duas características biométricas são extraídas a partir de imagens da mão: superfície da palma e superfícies dos dedos. Cada característica é extraída por meio dos algoritmos PCA, LDA e PCA-LDA, e processada individualmente. Por fim as diferentes modalidades são combinadas ao nível da pontuação numa só biométrica. É também feita uma análise mais aprofundada de diferentes metodologias (como medidas de distância, regras de fusão, métodos de normalização), juntamente com a comparação dos resultados experimentais derivados da variação de diversos parâmetros operacionais do sistema, como por exemplo o tamanho da área de interesse (ROI) extraída para cada biometria. Os resultados alcançados demonstram que a fusão biométrica tem um impacto bastante positivo no desempenho do sistema e que este sistema é adequado para aplicações de alta segurança, mesmo utilizando ROIs relativamente pequenas.

Palavras Chave

Biometria, reconhecimento de pessoas, superfície da mão, impressões da palma da mão, superfície dos dedos, fusão multimodal.
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List of Acronyms

DB       Database
DNA      Deoxyribonucleic Acid
DoS      Difference-of-Slopes
DPI      Dots per Inch
EER      Equal-Error-Rate
FAR      False-Acceptance-Rate
FRR      False-Rejection-Rate
FTE      Failure-to-Enroll rate
IR       Infrared
LDA      Linear Discriminant Analysis
PCA      Principal Component Analysis
PIN      Personal Identification Number
RGB      Red-Green-Blue image format
ROI      Region of Interest
USB      Universal Serial Bus
SVD      Singular Value Decomposition
1 Introduction

Traditionally, passwords or ID cards have been used for a wide range of security applications, ranging from border and airport security, time and attendance control, access to restricted areas, online banking, etc. These types of identity recognition methods present serious disadvantages, as they become less and less secure in a world where security threats are escalating (e.g. identify theft, terrorism).

The increasing need for improved and higher security systems has been accompanied by a continuous research and commercial growth of biometric-related technologies, being expected that the global biometric market is to grow at an annual rate of more than 20% through 2012, according to a new market research report [1].

Biometric recognition refers to systems that provide the automatic recognition of a person’s identity based on human physical, physiological or behavioural characteristics, such as features of fingerprints, face, hand geometry, iris or a person’s voice. The major advantage of biometric characteristics over traditional methods is that they are typically unique for each person and cannot be lost or as easily stolen or forged.

A recent study from 2007 regarding the current market shares of the major biometric technologies shows that hand-related biometrics account for at least\(^1\) 67% of the total market, as illustrated in Figure 1-1. This value is up from roughly 53% in 2006, when fingerprint-related technologies accounted for almost 44% and hand geometry for about 9%.

![Biometrics market share by technology, 2007. Study from the International Biometric Group [2].](image)

\(^1\) At least, since no mention is made in the study’s market share chart in what regards to palmprints.
There exist several different types of hand-related biometric characteristics. The current state of the art systems are based on: hand or finger geometry [3]; palmprint features [4]; fingerprints or finger surface analysis\(^2\) [5]; and vein patterns of the palm [6].

More recently, the last few years have seen the appearance of full hand biometric scanning devices (i.e. devices that behave as regular fingerprint recognition systems do, but scan the entire hand) and current research in biometric recognition has also focused on multimodal biometric systems that collect different biometric characteristics from an individual’s hand and through their fusion intend to improve the system’s reliability.

The work detailed in this document aims to build on previous research by the author in this area [7] and extend the study of topics that could be further explored. Another motivation is to provide a deeper analysis into different methodologies and algorithms, along with an in-depth comparison of experimental results derived from the variation of a wide range of system operating parameters.

It does not intend to be a direct continuation of the previous research work and therefore not all biometric characteristics present in the latter are used. The preceding work was aimed at building a multimodal biometric recognition system that encompassed three hand features obtained from one single sensing device: hand geometry, palm and finger surfaces. The first has been extensively studied in the literature and so is not included in this work. The last two however, more so the finger surfaces, are still a relatively new research area and are given a more extensive look in the current work.

This work’s ultimate goal is to take further steps forward in the improved development of a full hand recognition system, which does not require any special image acquisition equipment, and works in extremely flexible conditions, being able to recognize an individual once he/she naturally extends a hand in front of the biometric sensing device.

Important contributions are made regarding the removal of acquisition restrictions and hand feature points localization. Another significant aspect that is improved in this work is the level of understanding concerning the effect of a number of system parameters on the recognition rates. More importantly also the performance outcome using hand’s regions-of-interest that are resized to very small small sizes is analyzed, which will allow the future research and development of biometric systems that capture and attempt recognition on small hand images that are extracted from much larger and complex images.

\(^2\) Fingerprint recognition refers to the analysis of minutia points in traditional fingerprint images, whereas finger surface recognition denotes the analysis of skin texture of the entire finger-strip.
The state of the art on the subject of full hand recognition systems, regarding the biometric characteristics used, is summarized in Table 1-1.

<table>
<thead>
<tr>
<th>Biometric System</th>
<th>Year</th>
<th>Hand Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kumar et al. [8]</td>
<td>2003</td>
<td>HG PP FS</td>
</tr>
<tr>
<td>Ribaric et al. [9]</td>
<td>2005</td>
<td>HG PP FS</td>
</tr>
<tr>
<td>Kumar et al. [10]</td>
<td>2005</td>
<td>HG PP FS</td>
</tr>
<tr>
<td>Ribaric et al. [12]</td>
<td>2006</td>
<td>HG PP FS</td>
</tr>
<tr>
<td>Sanches et al. [7]</td>
<td>2008</td>
<td>HG PP FS</td>
</tr>
<tr>
<td>Ying et al. [13]</td>
<td>2007</td>
<td>HG PP FS</td>
</tr>
<tr>
<td>Yan et al. [14]</td>
<td>2008</td>
<td>HG PP FS</td>
</tr>
<tr>
<td>This work</td>
<td>2008</td>
<td>HG PP FS</td>
</tr>
</tbody>
</table>

Legend: HG – Hand geometry; PP – Palmprint features; FS – Finger surface features.

System spoofing attempts are solved in the literature [11] by using IR thermal images for aliveness detection.

The development of this work was done in MATLAB environment. MATLAB provides a set of tools and methods that greatly increase the ease of development and reduce implementation time of image processing projects.

This document is composed of five different chapters and one appendix. Chapter one, the current chapter, serves as an introduction and provides motivation to the problem at hand. In chapter two an overview of biometrics recognition and why it is useful is presented, along with a problem analysis and overall description of a hand-based recognition system. Chapter three includes a detailed description of the proposed recognition system, presenting algorithms and methodologies used throughout the entire recognition process. Test conditions and performance evaluation methods used are described in chapter four. In this chapter, the experimental results obtained are also presented and analysed. Chapter five provides conclusions and proposes future work. Finally, appendix A includes detailed test results.

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3 Only finger geometry features were used in this work.
4 In this work a distinction is made between the surface of the finger-strips and the digits.
2 Hand-based Biometrics Recognition

2.1 Biometrics Overview

Traditionally, user authentication systems have either been based on something one knows (e.g. a password, PIN code, personal information) or something one has (e.g. smart card, USB token) [15]. However, the information relied upon by the first method is susceptible of being forgotten or disclosed, while the second method has the disadvantage that objects can be stolen, lost or forged.

The use of biometric systems is a growing security method that is based on something one is or something one produces. This means of personal authentication does not only overcome most of the previously mentioned drawbacks, but is much more reliable and convenient. There are a variety of applications where biometric technologies have been successfully used in the real world. Examples range from improving forensic methods in criminal investigations, physical access control to restricted areas, employee attendance supervision and offering protection from identity theft in financial transactions, among others.

A biometric is defined as a measurable physical characteristic (e.g. fingerprints, facial features), physiological feature (e.g. DNA) or behavioural trait (e.g. voice patterns, gait), of an individual, that can be used for identity recognition purposes through statistical analysis.

Biometric systems work by using a reader or scanning device to capture an individual’s biometric characteristics and convert its unique features into digital data, normally called a template. This template is then enrolled into a database or some other secure storage location (e.g. a smart card) and later used for comparison with a new sample, to determine whether there is an identity match for recognition purposes.

The amount of data that is required to store a template is referred to as the template size. This size varies significantly based on the biometric modality being analyzed, technology employed and the biometric system’s vendor. For large biometric databases, a very small template size is desirable, because of both storage and processing speed restrictions.
The process through which a biometric system handles the long-term validity of templates, by taking into account the effects of changes over time on biometric data (e.g. growth of a child), is called template aging [16]. While one option is to regularly discard and replace old templates, another is to improve an existing template by adding or updating template information. An example of a template aging technique is to employ decay parameters that control the weight of different training samples according to their enrolment age, in order to mitigate the effects of variability over time [17]. Template aging might however not always be desirable or necessary and is not often a part of most biometric systems.

In biometrics there are two types of identity matching: identification and verification. Identification is a one-to-many comparison of an individual’s biometric sample against a template database of previously gathered samples. Verification refers to a one-to-one comparison between a previously acquired template of an individual and a sample which we want to authenticate. An application providing verification support would also require some other means for the user to claim his identity (e.g. information contained in a smart card, keyboard for user input), while for identification purpose this is not needed.

A different number of measures are generally used as biometric identifiers and may focus on a variety of unique human physical or physiological traits [18]:

- **Face Recognition** – shape, pattern and position of facial features.
- **Facial Thermography** – facial heat signature.
- **Fingerprint** – fingertip ridge patterns.
- **Hand Geometry** – shape of the hand and length of the fingers.
- **Palmprint** – ridges that exist on the palm of the hand.
- **Iris Scan** – features of the coloured ring of the eye.
- **Retinal Scan** – blood vessel patterns in the eye.
- **Vein Patterns** – vascular patterns of the hand/wrist.
- **DNA Recognition** – genetic data.
- **Ear Shape** – unique features of the geometry of the earlobe.
- **Dental Radiographs** – shape of the teeth.
- **Odour Recognition** – chemical composition of body odour.

Several behavioural biometrics measure different human actions, which have distinctive patterns from person to person:

- **Voice Patterns** – acoustic spectrum of the voice.
- **Keystroke Dynamics** – time spacing of typed words.
- **Gait Recognition** – movement of a person walking.
- **Signature Dynamics** – the way a person signs his/hers name.
- **Lip-reading** – lip movements of a speaker.
Purely behavioural biometric characteristics are usually not as accurate as physical or physiological ones, since not only are they easier to imitate and less time invariant, but can also be greatly affected by external influences (e.g. illness, mood).

No single biometric is optimal, each one having its weak and strong points. Although one feature may lack the uniqueness to distinctively differentiate between any two individuals, other characteristics can be used (e.g. eye colour, gender, height, skin colour) to complement the information provided by the usual biometric identifiers. These are usually called ‘soft-biometrics’, as defined by Jain et al. [19]. Search speed in large biometric databases can be dramatically increased through previous data filtering by means of soft biometrics and it can also be used to reinforce the correct identity matching of an individual.

Recent studies [20][21] show that multimodal biometric systems, which use more than one physical, physiological or behavioural characteristic for establishing an individual’s identity, have a much better performance than unimodal ones. Multimodal biometrics not only help to better prevent spoof attempts by imposters, but also increase recognition rates. Another benefit is that if for some reason biometric data from a given feature cannot be acquired, the biometric system is still left with the option of performing identity matching based on alternative biometric characteristics.

2.2 Problem Analysis

Four different types of biometric characteristics can be extracted from the hand: (i) hand geometry features such as hand shape, palm area, width and length of fingers and other measurements; (ii) palmprint characteristics like principal lines, wrinkles, feature points, and skin texture; (iii) fingerprint or finger-strip features, composed of the ridges, furrows and texture on the surface of the finger; (iv) and hand vein patterns.
Most features can be extracted from low-resolution hand images with less than 100 dpi, but in order to extract fingerprint characteristics and palm feature points, high-resolution images with a minimum of 400 dpi are required [8][22]. The analysis of vein patterns however requires very specific and expensive equipment, since it is based on thermal images captured by an infrared (IR) camera.

The inner finger-strip surface of the fingers has only very recently been a subject of research [9][11][12]. As happens for palmprints, the skin texture features of the inner surface areas of the fingers can be analyzed for uniquely identifying characteristics. These two biometric characteristics require relatively low cost equipment, are non-intrusive and very user friendly. The fact that they can also be acquired using a single sensing device is one of the major reasons for them to be the subject of study in this work.

A limiting factor for hand biometrics, may arise with users that suffer from arthritis or with other disabilities (e.g. people missing upper limbs or with limited hand use).

The architecture necessary for the generation of a user’s template by a biometric system is composed of a series of different blocks: a biometric sensor, which in this case is used for hand image acquisition; a pre-processing stage that handles such things as normalization, hand feature points calculation or noise reduction (e.g. shadows, digital image noise, dust/marks artefacts); and a feature extraction stage that outputs biometric templates based on features present in specific regions-of-interest on the hand. This architecture is illustrated in Figure 2-3.

![Figure 2-3 – Biometric template generation system architecture.](image)

A biometric system must also have a database where templates of enrolled users are stored. For the enrolment procedure a set of several hand feature templates might be acquired and stored for each user, depending on the number of training samples better suited for the recognition algorithms used.

Additionally it must allow for verification or identification queries, which requires the existence of another processing phase, called the matching stage. This stage is constituted by a block that provides similarity scores between the user’s template and all templates previously stored in the database, and a final block that, based on the best match’s score and system operating thresholds, decides if this is a valid match or not. This part of the architecture that deals with template recognition is illustrated in Figure 2-4.
The performance aspects of a biometric system can be affected by the reliability of the sensor and by the robustness and operating parameters choice of all its constituent processing stages.

In some cases the extracted features can have poor quality (e.g. due to a cut on a finger) or not be discriminating enough. This impact can be reduced by using different biometric characteristics in a multimodal biometric system. This leads to the introduction of a fusion stage that can potentially increase the probability of success and robustness of the biometric system (e.g., the above example of a cut on a finger surface would have no impact on palmprint features).

A fusion block is required not only for combining the information obtained from all five different fingers, but also to afterwards merge this with the data from the palmprint. An architecture that achieves this fusion is illustrated in Figure 2-5, being the actual block only shown for the fusion of the combined finger surfaces and palmprint modalities.
3 System Description

3.1 Image Acquisition

Hand images are acquired by means of a regular digital camera coupled with a tripod for image stability or by using a flatbed digital scanner.

Even though using the scanner for image acquisition has the advantage of constraining the hand to a more defined pose and providing higher-resolution images, it also has some disadvantages, in comparison to using a digital camera, that greatly impair its usability. Not only are the hand palm and fingers deformed due to compression against the scanner glass, but also the time needed for acquisition is never less than a few seconds (value which greatly increases for colour scans), which requires the user to hold the hand completely still during that time.

In contrast, a digital camera enables almost instantaneous acquisition of colour images. However, care must be taken to guarantee that hand images are in focus. This can be achieved by having a controlled acquisition environment, ensuring that hand pose and distance relative to the camera remain more or less constant between acquisitions.

To simplify the segmentation of input images in the pre-processing stage, hand images are acquired with the fingers spread apart and against a well defined background that contrasts with the skin colour. In this work a constant black background was chosen for this purpose.
As previously stated, most hand features, like shape and skin texture information, can be extracted from low-resolution images, but to extract fingerprint characteristics and palm feature points, high-resolution images are required. Due to the smaller file size, and therefore faster computation times, low-resolution images are more suitable for real-time biometric systems.

Hand images used in this work range from resolutions of 70 dpi up to 180 dpi, depending on which database is used, while image dimensions vary from 1280x960 to 2272x1704 pixels.

3.2 Pre-processing

Following acquisition, the captured image is pre-processed in order to segment the hand image from the rest of the image constituents, so as to obtain the hand shape contour and feature points. The resulting information can then be used as input to subsequent processing stages.

The hand feature points are comprised of relevant fixed locations that can serve as a reference for locating the palm and finger surfaces. As can be seen in Figure 3-2, these are constituted by the five fingertips (shown as red dots), the four finger-webs (marked as green dots) and three other additional auxiliary points (displayed as yellow dots).

![Figure 3-2 – Hand contour and feature points.](image)

3.2.1 Image Adjustment

The first step in the pre-processing stage is to do a colour space conversion on the input image from RGB into greyscale. This is achieved by retaining only the luminance information, which is enough for image segmentation of non-complex scenes (i.e. with a constant background), while hue and saturation are discarded. There exist however other image segmentation algorithms not explored in this work that rely on the colour information.
Next the image is resized to significantly lower dimensions, without changing its aspect ratio, using nearest neighbour interpolation. In this work the scaling factor is such that the output image will have no dimension greater than 256 pixels. This scaling step is necessary to reduce the computational effort associated with the rest of the pre-processing stage, having however no significant impact in the image segmentation accuracy. This resized image is only used for pre-processing purposes, being the original image the one that is used in the feature extraction stage.

Finally, to eliminate image noise, a low-pass filter is applied on the scaled intensity image, so as to smooth areas with little variance while still preserving edges. In this work an adaptive Wiener method based on local pixel-neighbourhood statistics was chosen for filtering. The resulting greyscale image is shown in Figure 3-3.

![Figure 3.3 – Image adjustment for pre-processing stage.](image)

### 3.2.2 Image Segmentation

Next, the image is segmented into foreground and background. Given an input image with constant background, as is the case for this work, the hand region can be distinguished by using an automatic global histogram thresholding technique. This is done by applying Otsu’s method [23], which chooses the threshold value that minimizes the intra-class variance of the output binary image, as can be seen in Figure 3-4.

![Figure 3.4 – Automatic image binarization using Otsu’s method.](image)

Using an algorithm based on morphological reconstruction [24], a flood-fill operation on background pixels is then applied in order to fill any holes which might eventually be present.
in the foreground of the segmented image. Finally, as shown in Figure 3-5, the hand segmentation is achieved by labelling all the objects left in the image and masking out all but the one with the largest area, which is considered to be the hand, since all the input images are acquired in a controlled environment.

![Figure 3-5 – Image segmentation and labelling.](image)

### 3.2.3 Hand Placement Verification

Subsequently, the resulting image is analysed for incorrect hand placement, ensuring that only valid input images are processed in the following stages. Hand placement is considered correct when the hand region is entirely captured (i.e. fingertips and palm region are completely inside the boundaries of the acquired image).

In order to accomplish this, the hand shape’s convex image, which is its convex hull [25] with all pixels within the hull filled in, is checked not to cross more than two continuous image borders. Care is taken not to exclude hand images that have small holes adjacent to the image edges (due to clothing, light conditions, etc). The difference between correct and incorrect hand placement is visually shown in Figure 3-6.

![Figure 3-6 – Check for correct hand placement.](image)
The verification method explained above not only allows the acceptance of images where the arm or wrist region crosses one or two image edges, but also admits images where no edge is crossed. This later scenario might happen for example due to skin occlusion on the wrist or arm areas (usually caused by watches, bracelets or clothing), as seen below in Figure 3-7.

![Figure 3-7 – Captured hand image with no edge crossings.](image)

### 3.2.4 Hand Contour Tracing

The next step is to trace the outline contour of the hand shape, as illustrated in Figure 3-8. A popular algorithm [26] to extract the contour is to begin at an initial point, which can be any point on the hand binary boundary, and then search for all subsequent adjoining boundary pixels in a clockwise or counter-clockwise direction.

![Figure 3-8 – Contour tracing of hand boundary pixels.](image)

Having found the hand contour, this information can then be used as a boundary reference in later processing stages, aiding for example in the calculation of regions of interest for features extraction. It could also be used as a basis for biometric hand shape analysis and comparison, as is done in [3].

### 3.2.5 Feature Points Determination

To find the hand feature points location based on the hand contour, two plot analysis techniques are commonly applied: radial distance to a reference point [3][27] and contour curvegram [3]. Both these methods allow the identification of the hand five fingertips and four finger-webs, having each its advantages and disadvantages.
3.2.5.1 Radial Distance to a Reference Point

The first method works by analyzing the Euclidean distance between the sequence of hand contour pixels and a reference point. Usually, the middle point of where the arm or wrist region crosses the image edge is chosen as the reference point [3], since due to the hand’s shape, this is the reference that better accentuates the desired hand feature points. However, as stated previously, some hand images do not contain any edge crossing, being a solution for this problem explained in a later chapter.

A radial distance plot, which can be easily analysed for local maxima and minima, is then constructed. In Figure 3-9, the reference point is shown as a red cross along the contour points. The five fingertips corresponding to the local maxima are marked as red circles in the distance plot, whereas the four finger-webs that correspond to the local minima are marked in green.

This method has however some disadvantages. It is not very precise, since the accuracy of feature point locations can be affected by orientation differences between the arm region and the hand, as happens in Figure 3-10.
In this example it is perceivable that some of the fingertips and all of the fingerwebs are slightly deviated from their correct locations. Such deviations could have serious impacts on the performance of biometric recognition systems, not only for hand geometry, but also for all other hand biometrics, since the identification of regions-of-interest is based on these feature points.

Another major disadvantage of this technique is that the arm or wrist location must be known beforehand. Since in this work no restriction is placed on the number of image edges crossed by the hand shape, as seen in chapter 3.2.3, this location might not be straightforwardly identifiable for all images.

### 3.2.5.2 Contour Curvegram

The second method analyzes the profile of the curvature along the contour, also called the contour curvegram, which can be constructed by using a technique called Difference-of-Slopes (DoS) [3][28].

This technique consists in running along the contour with two vectors, one before and one after the current contour point being analysed, as can be seen in Figure 3-11, and calculating the angle difference between these two vectors.
Let \( \mathbf{v}_1 \) and \( \mathbf{v}_2 \) be two vectors in Euclidean space, then the angle \( \theta \) between them, is related to their dot product and their lengths by the equation:

\[
\theta = \cos^{-1}\left( \frac{\mathbf{v}_1 \cdot \mathbf{v}_2}{\|\mathbf{v}_1\|\|\mathbf{v}_2\|} \right)
\]  

(3.2-1)

The angle \( \theta \) is in the range \([0 \ldots \pi]\), but to differentiate between fingertips and finger-webs one must also determine if it is a positive or negative angle. This can be achieved by analyzing the sign of the \( z \)-coordinate of the cross-product between \( \mathbf{v}_1 \) and \( \mathbf{v}_2 \). If the sign is positive, the rotation must have been anti-clockwise and so the angle is positive, otherwise it is negative. Thus, a more complete formula of the difference-of-slopes value for any contour point is given by:

\[
\theta = \text{sign}((\mathbf{v}_1 \times \mathbf{v}_2)_z) \cos^{-1}\left( \frac{\mathbf{v}_1 \cdot \mathbf{v}_2}{\|\mathbf{v}_1\|\|\mathbf{v}_2\|} \right)
\]  

(3.2-2)

In this work the end point of a vector was empirically set to lay 32 contour points after its beginning, which is of course directly linked to the input image size, since this was the value that achieved better output plots during the tests. For low vector length values, the output plot is extremely noisy due to increased sensitivity to small contour slope changes, whereas for high values it is not discriminating enough, as can be seen in Figure 3-12.
The output plot from this method is very noisy, since it is much more susceptible to contour irregularities than the radial distance method. In order to smooth it, a convolution is done with a Gaussian window of the same size as the vectors. Figure 3-13 shows a curvegram plot, with the five fingertips marked as red circles and the four finger-webs in green. These correspond to the most prominent local maxima and minima respectively.
As happens for the radial distance method, under non-ideal conditions the arm or wrist location must be known beforehand for this method to work correctly. Contour “disturbances” (e.g. a bracelet) might make it extremely difficult to robustly distinguish the hand feature points from other undesirable features, as can be seen in Figure 3-14.

![Figure 3-14 – Presence of undesirable features in curvegram caused by a bracelet.](image)

This method has however the great advantage of being invariant to rotation and not having to rely on a reference point.

### 3.2.5.3 Two-step Approach

To overcome the limitations from each of the previously explained methods, it is advantageous to use a combination of both.

First the radial distance is used to obtain not very precise points, but without any false matches due to contour noise. Then the contour curvegram is examined around these locations in order to obtain more accurate positions. The extracted minima and maxima points will be the final fingertip and finger-web locations.

In order to use this combined approach, a suitable reference point must first be found for using the radial distance method. In order to achieve this, the ellipse that has the same normalized second central moments as the hand region [30] is analysed.

As is shown in Figure 3-15, several parameters are calculated: the ellipse’s major and minor axes’ end-points and lengths, shown in green and cyan respectively; its orientation, i.e. the angle between the x-axis and the major axis of the ellipse; and also its centre.
Having found the defining parameters of the ellipse, there is still one very important thing that needs to be determined: on which side of the major axis of the ellipse is the arm or wrist region located. This can be determined by counting the number of contour points which lie on each side of the hand shape. The points that divide the hand shape in two, marked as cyan crosses in Figure 3-16, are the contour points which are closest to the minor-axis’ end points.

For any hand shape, the total number of contours points present in the part of the contour profile where the fingers are located, shown in blue in the figure above, is approximately double the number of contour points of the opposite part, which is shown in red and where the arm or wrist region is located.

Knowing this information, the contour point that is closest to the major-axis’ end point which lies on the arm or wrist region, shown as a green cross in Figure 3-17, is considered as the reference point for the radial distance method.
The final approach for finding the hand feature points, that can be seen in Figure 3-18, consists of: first calculating the ellipse that has the same normalized second central moments as the hand region; then based on that information and on the contour, obtaining a reference point on the arm or wrist region; analyzing the radial distance plot of the contour to this reference point to extract approximate locations for the feature points; and finally, analyze the contour curvature profile around these locations to obtain more precise locations for the feature points.

3.2.6 Distinguishing Left from Right Hands

The next step is to determine if the hand shape under analysis is that of a right or left hand. This is accomplished by determining which of the outer fingers has the greatest width at its middle, as can be seen in Figure 3-19, where the fingers’ widths are marked as yellow dotted lines. The thumb will always have a width greater than the pinkie finger.
This is important not only for the extraction of additional hand feature points, but also to serve as a “handness” flag in the matching stage, helping to greatly reduce the number of needed comparisons, thus decreasing computation times. By using this flag, a right hand input image need only be compared against feature templates from right hands.

### 3.2.7 Additional Feature Points

Three other additional feature points on the hand are also computed to help delineate the limits of the fingers, which is not only helpful for hand geometry measures, but also for the extraction of the regions-of-interest of the palmprint and finger surface areas.

These additional reference points are found by discovering, for the thumb, index and pinkie fingers, the contour point that has an Euclidean distance to the fingertip equal to the distance from the fingertip to the finger-web, as is shown by the yellow dotted lines in Figure 3-20.

The final set of hand feature points, as shown before in Figure 3-2, consists of the five fingertips, four finger-webs and the calculated three additional reference points.
3.3 Feature Extraction

3.3.1 Hand Regions of Interest

A recent trend in biometric systems for features extraction on hand images is the statistical analysis of skin surface data. Several techniques have been actively researched in the past, mostly for application in face recognition systems. Among these are methods like Principal Component Analysis [31] and Linear Discriminant Analysis [32].

The first step required for feature extraction from hand skin areas is to extract the region-of-interest (ROI) from the input hand image, so that the skin surface data can be converted into a numerical feature template.

The ROI for palmprint recognition purposes is usually a square region in the central part of the palm, even though a technique that divides the palm region into several sectors of elliptical half-rings has also been presented in the literature [33].

To obtain the palm’s ROI, the hand feature points calculated in the pre-processing stage are used as a reference. As illustrated in Figure 3-21, the middle points of two line segments that lay between the beginning of the index and pinkie fingers are used as vertices of a square region of the palm [31] from where features will be extracted.

The ROI area will be of diverse sizes and orientations for different input images, thus requiring a normalization step. To this purpose, the ROI is first rotated to vertical orientation, converted to greyscale and finally resized to a standard dimension, so that features can be accurately extracted and compared with other samples. As a final step, the ROI image is changed into a template vector consisting of luminance values. This template vector is then used as input for the statistical analysis algorithms that linearly transforms it into a more discriminating feature space.

![Figure 3-21 – Palm’s ROI and template vector extraction.](Image)
The ROI standard size reported in the literature, and by result the template vector, ranges from sizes of 64x64 [9][34], up to 150x150 [35] and even 300x300 pixels [8], depending of course on the hand’s input image size. The smaller the ROI size, the less processing considerations (e.g. speed, memory limitations) have to be taken into account, although recognition performance might also be reduced. In this work several sizes are used for testing and comparison.

For obtaining the ROI for each finger’s inner surface, a similar procedure is followed. Again based on the hand feature points calculated in the pre-processing stage, the largest rectangle area lying inside the contour of each finger in a region bounded at 1/8 and 7/8 of its length is found. The set of finger surface ROIs, constituted by rectangular areas for the thumb, index, middle, ring and pinkie fingers, is shown in Figure 3-22.

Exactly as for the palm, the image of each finger’s ROI is normalized for rotation, colour space and size. Finally, the ROI image is also vectorized into a template consisting of luminance values.

The standard ROI size typically used in the available literature ranges from 64x16 [9][11] to 128x32 [12]. In Ribaric et al. [9][11] a distinction is actually made between the sizes used for the of pinkie and thumb fingers, which are 64x16 pixels in size, and the ring, middle and index fingers, which are of size 64x14. For testing purposes, in this work ROIs are resized to a number of different sizes.

### 3.3.2 Principal Component Analysis

*Principal Component Analysis (PCA)* is a commonly used technique for reducing data dimensionality [31]. It is nothing more than an optimal linear transformation that projects possibly correlated data from an original data space to a subspace composed by a number of uncorrelated variables, usually called principal components. The first principal component
will be the one that accounts for the most variability in data, and each subsequent component for a decreasing part of the remaining variability.

The lower dimensional-space that preserves the most information is the one that is centred on the sample mean and has directions determined by the eigenvectors of the sample’s covariance matrix corresponding to the highest eigenvalues. A more in-depth explanation is given in the next paragraphs.

If the training dataset is constituted by \( N \) template column vectors, each of size \( D \):

\[
x = \{ x_i \}_{i=1}^{N}
\]

then, the mean vector of the dataset will be given by:

\[
\bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i
\]  

(3.3-1)

The difference vector from the mean for each template is computed as:

\[
d_i = x_i - \bar{x}
\]  

(3.3-2)

Having a zero template mean dataset is a necessary assumption for the algorithm’s further calculations [36]. To obtain the covariance matrix that characterizes the data scatter, the following formula is then applied:

\[
C = \frac{1}{N-1} AA^T
\]  

(3.3-3)

, where \( A = [d_1 \quad d_2 \quad \ldots \quad d_i]_{i=1\ldots N} \).

Since the covariance matrix is a square symmetric matrix, an orthogonal basis can be calculated by finding its eigenvalues \( \lambda = \{ \lambda_m \}_{m=1\ldots D} \) and eigenvectors \( W = \{ w_m \}_{m=1\ldots D} \), being the latter also called the principal components. Then, to reduce dimensionality, only the eigenvectors corresponding to the highest \( K \) eigenvalues are chosen. The lowest eigenvalues can be ignored since even though some information is lost, it is not very significant for recognition purposes.

A matrix constituted by the chosen eigenvectors, ordered by magnitude of its eigenvalues, is called the reduced eigenspace \( W = [w_1 \quad w_2 \quad \ldots \quad w_m]_{m=1\ldots K} \). As a final step, a new
sample dataset is derived from the original dataset, by projecting the previously mean adjusted data vectors, via the linear transformation matrix $W$, into the new reduced subspace. Given an input vector $x_i$, its projection $y_i$ into the lower-dimensionality subspace is given by:

$$y_i = W^T x_i$$  \hspace{1cm} (3.3-5)

In this work, tests were run with a varying number of total highest eigenvalues and corresponding eigenvectors used for formation of the reduced eigenspace.

When a vector from the test set is compared against another from the training dataset, first its difference to the train dataset’s mean vector needs to be calculated and then it must be projected into the reduced subspace. Comparison is done against the already projected vectors of the training dataset.

The PCA transformation is easily understood with the aid of a graphical representation example for a two-dimensional dataset. As illustrated in Figure 3-23, the principal component vectors $v_1$ and $v_2$ best capture the variance of the original dataset, accounting $v_1$ for the most data variability. These principal component vectors describe an orthonormal basis that is effectively a rotation of the original cartesian basis.

![Figure 3-23 – Visual representation of a PCA transformation in only two dimensions. Image taken from [37].](image)

Calculation of the covariance matrix can however become, for large template sizes, not only very memory consuming, but also extremely expensive in terms of processing time, as illustrated in Figure 3-24. For example, a 256x256 region-of-interest ($M \times M$) would originate a covariance matrix of size 4,295,000,000.
As stated previously, only the highest eigenvectors of the covariance matrix $C$ contain important information, the rest is zero or close to zero. It has been proven [38] that the eigenvectors of $A^T A$, which is of significantly smaller dimension ($N \times N$), will be the same as the highest eigenvectors of $A A^T$. As an example, a sample database of $N = 500$ training templates would originate a matrix of size 250,000.

**Singular Value Decomposition (SVD)** is a matrix factorization technique that can be applied here for solving this new problem. According to SVD [39], a matrix can be decomposed in the form:

$$A = USV^T$$  \hspace{1cm} (3.3-6)

, where $S$ is a diagonal matrix and $U$ and $V$ are both orthogonal.

It can thus be shown that:

$$A^T A = VS^2 V^T$$  \hspace{1cm} (3.3-7)

Therefore, the relation between PCA and SVD [39] is that the square root of the eigenvalues are the singular values along the diagonal of $S$, and that $V$ corresponds to the eigenvectors of $A^T A$.

The great advantage of SVD is that there exist a large number of algorithms for computing it, some of which are extremely fast by allowing the calculation of only the highest $K$ eigenvectors.
3.3.3 Linear Discriminant Analysis

*Linear Discriminant Analysis (LDA)* is a dimensionality reduction technique that is used to project a high-dimensional original space into a significantly lower dimensional feature space, in which class separability is maximized [40]. The class separability is defined as the ratio of the between-class scatter to the within-class scatter. In other words, it tries to group samples of the same class closer together while separating samples of different classes further apart.

PCA is based on the sample covariance which characterizes the scatter of the entire dataset irrespective of class-membership and therefore not always the optimal technique for classification purposes. In opposition, LDA takes into consideration class discriminatory information, and thus tries to seek the directions along which the classes are best separated, as illustrated in Figure 3-25 where the projection that achieves greater class separability is the one represented by the subspace projection $W_1$.

![Figure 3-25](image.png)

*Figure 3-25 – Three-dimensional distributions projected into two-dimensional spaces. Image taken from [41].*

For a non-ideal dataset of samples, customarily the objective is to minimize the overlap between the projected sample classes, since no projection can usually be found that completely separates them.

Let there be a set of $N$ sample data column vectors, of equal dimension $D$ each:
\[ x = \{x_i\}_{i=1}^{N} \quad (3.3-8) \]

If there are \( K \) classes \( \{C_j\}_{j=1}^{K} \) in this dataset, containing \( N_j \) samples each, then the mean of a given class is:

\[ \bar{x}_j = \frac{1}{N_j} \sum_{x_i \in C_j} x_i \quad (3.3-9) \]

The total mean of the dataset is:

\[ \bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i \quad (3.3-10) \]

The scatter matrix of a particular class, which measures the spread of data around the mean and whose formula, apart from a scale factor is the same as for the covariance matrix, and is defined as:

\[ S_j = \sum_{x_i \in C_j} (x_i - \bar{x}_j)(x_i - \bar{x}_j)^T \quad (3.3-11) \]

Obtaining the within-class scatter matrix, which is both symmetric and positive semi-definite and therefore with all non-negative eigenvalues, is accomplished by summing for all classes:

\[ S_W = \sum_{j=1}^{K} S_j \quad (3.3-12) \]

Finally, the between-class scatter matrix, that is also symmetric and positive semi-definite, is calculated according to:

\[ S_B = \sum_{j=1}^{K} N_j (\bar{x}_j - \bar{x})(\bar{x}_j - \bar{x})^T \quad (3.3-13) \]

The idea is to project the sample data vectors, via a linear transformation matrix \( W \), into a lower-dimensional space. The mapping of an input vector \( x_i \) into the projection subspace is given by:
\[ y_i = W^T x_i \]  \hspace{1cm} (3.3-14)

The determinant of a matrix is the product of its eigenvalues, and so it can be used as a simple measure of scatter [42]. Therefore, the transformation matrix that most separably repositions the sample data is given by a maximization of the ratio of the determinants of the between-class and within-class scatter matrixes, \( \tilde{S}_B \) and \( \tilde{S}_W \) respectively, of the projected samples:

\[
J(W) = \frac{\left| \tilde{S}_B \right|}{\left| \tilde{S}_W \right|} = \frac{|W^T S_B W|}{|W^T S_W W|} \hspace{1cm} (3.3-15)
\]

Thus, the optimal discriminating projection will be found by maximizing the above objective function:

\[
W_{opt} = \arg \max_W J(W) \hspace{1cm} (3.3-16)
\]

Obtaining a solution to the classical Fisher’s criterion defined above is equivalent to solving a generalized eigenvalue problem:

\[
S_B W_{opt} = \lambda S_W W_{opt} \hspace{1cm} (3.3-17)
\]

The elements of the diagonal matrix \( \lambda = \{\lambda_m\}_{m=1}^D \) that satisfy the previous equation are called the \textit{generalized eigenvalues} and the optimal projection matrix is composed by the corresponding \textit{generalized eigenvectors} \( W = [w_1 \ w_2 \ \ldots \ w_m]_{m=1}^D \).

If the within-class scatter matrix is non-singular, the generalized eigenvalue problem can be converted into a standard eigenvalue problem:

\[
S_W^{-1} S_B W_{opt} = \lambda W_{opt} \hspace{1cm} (3.3-18)
\]
Since the between-class scatter matrix has a maximum rank of $K - 1$, there can only be at most $K - 1$ distinct non-zero solution eigenvalues [43].

On the other hand, the maximum rank of the within-class scatter matrix is $N-K$. Since usually for high-dimensional problems, the number of training samples is much smaller than the dimension of the sample vectors, $N\ll D$, we have a dataset that is severely under-sampled. In these cases the within-class scatter matrix is singular and the generalized eigenvalue problem cannot be converted into a standard problem.

Even if the within-class scatter matrix is non-singular, under the condition that the ratio of the number of training samples $N$ to the samples dimension $D$ is not large enough, know in the literature as the small sample size problem, it will be unstable [44][45].

Several approaches have been reported in the literature to solve the singularity and instability problems related to the within-class scatter matrix:

- Increase the number of samples in the training set;
- Reduce the size of the sample vectors;
- Project the samples into a reduced dimensional space beforehand [38];
- Stabilize the within-class scatter matrix by regularization [38].

This problem can happen for example for a small ROI size of $64 \times 64$, which when vectorized produces a $D = 4096$ dimensional vector. A combined PCA-LDA approach has been widely used in face recognition to solve this problem [46]. PCA is often used for first projecting the vectors into a lower dimensional subspace, effectively reducing the dimension of $x_i$ from $D$ to $N - K$, and then LDA is applied to maximize discrimination and further reduce the dimension to $K - 1$, producing a non-singular and stable within-class scatter matrix.

As happens for the PCA method, processing times and memory consumption requirements grow in accordance with the template sizes, being the PCA-LDA method also a good solution for this specific problem.

Tests for LDA were run with a varying number of total highest eigenvalues and corresponding eigenvectors. Also, when comparing a test set vector to one from the training dataset, first it has to be projected into the reduced subspace. The comparison is then done against the already projected training vectors.
3.4 Matching

The matching stage provides the means to determine the identity of a user. When a user attempts recognition in a biometric system, the user’s generated features template will be compared against the templates stored in the database.

In one-to-one verification, this comparison is done only against the claimed identity’s template, whereas in a one-to-many identification it is done against the entire database. Since the case of verification is just a subset of the identification case, only the later is described and reported in this work – verification will typically yield better results.

The matching stage is based on a classification algorithm that generates a distance score for each template comparison using a feature vectors’ similarity measure. The score with the lowest distance value indicates the best match. Unnecessary template matching comparisons are avoided by also taking into account if the templates being compared both belong to the right or left hand, information which is obtained from the pre-processing stage.

After running the matching algorithm, a recognition decision is made whether to accept or reject the best match found. If the distance score exceeds a predefined threshold, the recognition attempt is considered as an imposter access, otherwise the recognition attempt is considered a client access and the system assumes the user has been correctly identified. The classification procedure is illustrated in Figure 3-26.

![Figure 3-26 – Template matching against templates in a database.](image)
Many distance measures exist that evaluate the similarity between a pair of vectors. In this thesis, a number of such metrics are applied for classification purposes and their results are compared.

Let \( x = [x_1 \ x_2 \ \ldots \ x_n]_{n=1\ldots N} \) be the feature vector of a user attempting recognition and \( y = [y_1 \ y_2 \ \ldots \ y_n]_{n=1\ldots N} \) a database template vector being used for comparison, where \( N \) is the number of elements in each vector.

The *Euclidean or L2 distance* between the two vectors, measuring the shortest possible path between them in Euclidean space, is given by:

\[
D(x, y) = \sqrt{\sum_{i=1}^{N} (x_i - y_i)^2}
\]

A closely related measure is the *Manhattan or L1 distance*, which examines the absolute difference between coordinates of two vectors. This distance is defined as:

\[
D(x, y) = \sum_{i=1}^{N} |x_i - y_i|
\]

The difference between the Manhattan and Euclidean distances between vectors in a two dimensional space is illustrated in Figure 3-27.

Another measure of vector pairwise distance is the *Cosine distance*, that classifies based on the cosine angle between the vectors, which is given by\(^5\):

---

\(^5\) Formula used in MATLAB’s Statistical Toolbox for cosine distance calculation.
As described before, the recognition decision is usually made taking into account the best match found. Another alternative is to employ the \( k \)-Nearest Neighbours algorithm, which is also a fairly simple classification method.

This method works by classifying a sample based on the majority vote of its neighbours, being the chosen class the one which is most common amongst its \( k \) nearest neighbours, as shown in Figure 3-28. This classification is usually based on the Euclidean distance between the sample and database template vectors, although any other distance measure might be used.

In the illustrated example, the sample is matched against all database templates whose distance measure is above the predefined threshold. For the case when \( k = 1 \), this method is exactly the same as the best match classification. In order for this method to work correctly, the existence of at least \( k \) training samples for each class is required.

### 3.5 Fusion

Recently the interest in multimodal biometric systems has increased, with the results showing that this is a worthwhile investment and promising research area. A multimodal biometric system requires an integration of the individual data of the various biometric modalities at some point in the processing stage.

Four different levels of fusion can be identified [47][48], as illustrated in Figure 3-29:
• **Sensor Level Fusion** – Sensor level fusion corresponds to sensing the input signal with more than one sensor. This is usually applied to unimodal systems, like for example speech recognition, where the speech signal can be captured by separate microphones. This type of data fusion brings advantages such as information redundancy and improvements for noise cancellation.

• **Feature Level Fusion** – This method is used, for example to combine multiple views of the same feature. A good example is the integration of multiple 2-D view features representing a 3-D image seen from different viewpoints and from different sensors.

• **Score Level Fusion** – This kind of fusion is also known as confidence level fusion. The scores from each of the individual biometrics are considered and combined to provide a single decision score. When combining the outcomes of different biometrics a common domain should be used, thus requiring normalization of the score distributions from the different matching blocks into a common range.

• **Decision Level Fusion** – At this level each individual biometric scheme provides an acceptance or rejection decision. A majority vote scheme is then applied; therefore fusion of this type is not appropriate for bimodal systems, since the final score may be a tie.

Figure 3-29 – Levels of biometric data fusion. Image taken from [47].
Also, in a multi-biometric system the fusion techniques can be applied in five different scenarios as illustrated in Figure 3-30:

- **Multiple sensors** for acquiring a single biometric modality.
- **Multiple algorithms** for feature extraction. In this scenario, templates with different information are created.
- **Multiple instances** of the same biometric modality, from equivalent but distinct body parts (e.g. right and left eye, different fingers).
- **Repeated instances** of the same biometric modality.
- **Multiple traits** combining features from different biometric characteristics.

![Figure 3-30 – Scenarios of biometric data fusion. Image taken from [47].](image)

In this work, both multiple traits and multiple instances scenarios are present. All five finger instances are considered for fusion purposes and two different biometric characteristics (i.e., palmprint and finger surface) compose the multiple traits scenario.

To combine the scores of the various fingers, the average score is found. In this case, there is no need for any score normalization, since all fingers already have scores in the same common domain.
On the other hand, the outputs of the palmprint and finger surface modalities are not homogeneous, making it necessary to normalize their scores into a common domain. Normalizing so that the score ranges are equal can be done in several different ways, being the most usual [49]:

- **Divide by Maximum** – values are scaled such that the largest value for each modality becomes one.

  \[ s' = \frac{s}{\max(s)} \]  
  \[ (3.5-1) \]

- **Min-Max** – values are scaled such that the smallest value for each modality becomes zero and the largest value becomes one.

  \[ s' = \frac{s - \min(s)}{\max(s) - \min(s)} \]  
  \[ (3.5-2) \]

- **Z-Score** – values are scaled such that each modality has an average of zero and a standard deviation of one.

  \[ s' = \frac{s - \mu}{\sigma} \]  
  \[ (3.5-3) \]

, where \( s = \{s_k\}_{k=1..n} \) are the distance scores for each modality, \( \mu \) its average and \( \sigma \) its standard deviation.

After normalization there must be a way for combining the common domain scores. One way is to find the scores mean value as was done here for the fingers. For the fusion of the palmprint and finger surface modalities, four different fusion rules were used for testing and comparison [50]:

- **Product rule** – the new score is the product of all the modalities scores.

- **Sum rule** – the new score is the sum of all the modalities scores.

- **Max rule** – the new score is the maximum score of all the modalities scores.

- **Min Rule** – the new score is the minimum score of all the modalities scores.

Test results for all fusion rules and normalization algorithms are presented in the following chapter.
4 Experimental Results

4.1 Test Conditions

Several different databases were used in this work, ranging from very small databases to relatively large ones. When images of both hands are available, they are treated as separate users for testing purposes and referred as such throughout this work.

All the images, of the different databases used, follow the requirements of having a constant black or dark background and having the fingers spread apart.

A small database of 11 users created at Instituto Superior Técnico was used, containing both left and right hand images in a total of 101 images. This database’s images include a coin in the background, leaving the possibility to use it as a size reference in future work. Images were acquired in colour with digital cameras. This database is identified in the rest of the document as “IST”.

The UST Hand Image Database [51], a popular hand image database available on request from the Hong Kong University of Science and Technology, which is widely used by the research community for testing hand biometrics, was also utilized and is very useful for comparing results. This database consists of 564 different users with 10 images per user, containing images of both hands, coming to a total of 5640 images. As for the previous database, images were also acquired with a digital camera and in colour. In the rest of the document, this database is referred to as “UST”.

Another small database used was a sample hand database from the University of Zagreb, mentioned from now on as “Zagreb”, consisting of 4 images of the right hand of 10 different users, for a total of 40 images. The images were collected with a scanner and are in greyscale. Images in this database however suffer from lack of uniform lighting conditions, causing sometimes backgrounds that are not constant and do not contrast well with the hand.

Finally, an average size database from the University of Las Palmas of Gran Canaria [52] was also used, referred as “LasPalmas” in the remainder of this document. This database has a total of 500 images, consisting of 10 right hand images of 50 different users. These images were also acquired with a digital scanner and are available only in greyscale.

An example image from each database is displayed in Figure 4-1.
4.2 Performance Evaluation Criteria

The recognition results of a biometric system should be reported with commonly used performance evaluation tools to simplify system comparisons. There are many standard metrics for analyzing the accuracy and performance of a biometric system, being the most widely used ones described below.

Testing scenarios can be classified as online or offline, depending on whether the testing is done in the presence of human users or using a sample database previously acquired. For this work, test results are generated offline on several previously acquired databases that emulate real-world samples. These databases provide a good approximation for an online recognition scenario, since they include hand images containing artifacts (e.g. rings, watches) and place no hard restriction on hand orientation or positioning other than the need for the fingers to be spread apart.

An important metric is the Failure-To-Enroll (FTE) rate that states the portion of the population for whom the system fails to complete the enrolment process. This rate is sensitive to the constraints imposed for image acquisition and is important for evaluation of the robustness of the pre-processing stage’s algorithm and the ease of use of the biometric. It is defined as:

\[
FTE = \frac{\# \text{ failed enrolments}}{\# \text{ total enrolment attempts}} \times 100\% \tag{4.2-1}
\]

A recognition attempt generates one of the four possible scenarios, as shown in Figure 4-2. If an imposter attempts identification, the biometric system can accept or reject the imposters’ identity claim, based on the defined classification threshold. In the first case the imposter is falsely accepted, while for the second situation it is correctly rejected. On the other hand, if a genuine user attempts access and is correctly recognized, this will count as a correct acceptance, otherwise as a false rejection.
Ideally, the distributions of the matching scores for imposters and valid client users should not overlap, meaning there would exist a score threshold for which no false acceptances/rejections would be reported. On a real, and therefore imperfect, system these two distributions overlap, as illustrated in Figure 4-3.

Three important metrics that measure the performance of the system classification decision based on the recognition claim scenario (imposter versus valid client user) are detailed in the next paragraphs.

The False-Rejection-Rate (FRR) indicates the frequency of rejected users who are not imposters. It is one of the most important metrics in a biometric system, since the restriction of access to genuine users is a considerable flaw. It is calculated as:

\[
FRR = \frac{\text{# rejected genuine claims}}{\text{# total genuine access attempts}} \cdot 100\% \tag{4.2-2}
\]
Another important metric is the False-Acceptance-Rate (FAR), which expresses the portion of false identity claims that are incorrectly accepted, by so depicting the frequency of fraudulent accesses. It is defined as:

\[
FAR = \frac{\# \text{ accepted imposter claims}}{\# \text{ total imposter access attempts}} \cdot 100\% \tag{4.2-3}
\]

In a top security system (e.g. an airport, bank) the FAR value must be minimum or zero, which might lead to a high FRR value. Given that a user has the possibility of making multiple access attempts, a high FRR may however not be an important problem. In opposition, for some low security systems (e.g. access to an amusement park) the acceptance of a few users with a false identity due to a higher FAR might not be as important and not worth the FRR tradeoff.

Finally, the Equal-Error-Rate (EER) is defined as the rate at which the FAR is equal to the FRR. A very low number for ERR indicates a system with a good balance of sensitivity but is not necessarily the adequate operating point. Specific system requirements could have constraints for a low FAR or FRR value. A visual representation of the EER can be seen by overlapping the FAR and FRR plots, as illustrated in Figure 4-4.

![Figure 4-4 – FAR and FRR curves according to matching threshold. Image taken from [53].](image)

### 4.3 Pre-processing Results

The rate of failed enrolments is of great importance in a biometric system. It allows the evaluation of two different factors: ease of use; and robustness of the pre-processing stage. The number of images that fail enrolment because they do not pass the system’s image acquisition restrictions gives a sense of how user-friendly the system is. For all other images that conform to the system’s restrictions, the FTE should optimally be zero, otherwise meaning that the pre-processing stage is not good enough.
The enrolment of all database images produced the FTE rates shown in Table 4-1. Shown in that table is also the number of images conformant to the system restrictions, that failed the enrolment step for each of the databases tested.

<table>
<thead>
<tr>
<th></th>
<th>IST</th>
<th></th>
<th>UST</th>
<th></th>
<th>Zagreb</th>
<th></th>
<th>LasPalmas</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>%</td>
<td>#</td>
<td>%</td>
<td>#</td>
<td>%</td>
<td>#</td>
<td>%</td>
<td>#</td>
</tr>
<tr>
<td>Total FTE</td>
<td>1.98</td>
<td>2</td>
<td>7.09</td>
<td>400</td>
<td>15</td>
<td>6</td>
<td>0.2</td>
<td>1</td>
</tr>
<tr>
<td>Conformant</td>
<td>0</td>
<td>0</td>
<td>0.02</td>
<td>1</td>
<td>5</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Non-Conformant</td>
<td>1.98</td>
<td>2</td>
<td>7.07</td>
<td>399</td>
<td>10</td>
<td>4</td>
<td>0.2</td>
<td>1</td>
</tr>
</tbody>
</table>

As can be seen, the FTE rates are not completely perfect, being however noticeable that the vast majority of failed enrolments are due to images that do not conform to the system’s restrictions. These cases are caused by images where either the fingers are not spread apart or one of the fingers crosses the image edges, as illustrated by the examples in Figure 4-5.

A solution for these non-conforming cases is not easy. The case where fingers are not well spread apart can only be solved by a much more accurate and complex segmentation algorithm, which of course will impact processing times.

As for the case where some fingers are not completely captured in the image, this is a problem of the image acquisition setup not being totally user-friendly. A not very good solution would be to impose further restrictions on hand placement by physically forcing the user to position the hand entirely within camera view. This is however against the goal of having an optimal hand recognition system, as described in the introduction chapter.

A better solution would be to have an acquisition setup that could segment a user’s hand from a larger and certainly complex input image, thus eliminating the need for
having a restricted area of capture. Again, this would require a better segmentation algorithm and would introduce other problems such as possible hand occlusion or pose variations.

The number of images that conform to the system’s restrictions but still fail enrolment is extremely small, although not totally negligible. A couple of examples are illustrated in Figure 4-6.

![Figure 4-6 – Failed images that conform to the system’s restrictions.](image)

As can be seen, in these examples, the images fail for two different reasons. In the “Zagreb” database (image on the left) failure is due to the biometric sensor being used – in this case a digital scanner – for which the lighting conditions are not optimal, creating a background that doesn’t contrast very well with the hand. The consequence is that the segmentation algorithm used, developed assuming a constant and contrasting background, is not appropriate to deal with this type of images and should be improved to account for these image acquisition conditions.

In the “UST” database, the only conformant image that fails enrolment is because of the fact that the pre-processing stage fails when trying to distinguish between left and right hand. Due to the placement of the hand, slightly rotated, the algorithm obtains equal widths, at their middle of both outer fingers. As can be seen in the right image above, this happens because the thumb finger is not well spread apart from the rest of the fingers, thus causing the algorithm to consider its middle point closer to the fingertip than it actually is.

Overall the pre-processing stage is very robust and flexible, coping easily with images containing artefacts (e.g. rings, bracelets), additional smaller objects (e.g. coins), any arm orientation or even no edge crossing by the arm region. Illustrative examples are shown in Figure 4-7.
4.4 Recognition Results

Detailed results for all databases can be found in the annex. In the current chapter, and analysis of the results is made, taking into account effects such as fusion, operating parameters variation, different methods and differences between the various modalities.

For the recognition results presented in this chapter, unless otherwise stated, the training set size is 5 for all databases except the “Zagreb” for which it is 2 – these values represent half the number of image samples for each user in each database. The remaining images are used for the test set. Also, unless otherwise mentioned, tests are done with a value k=64 eigenvectors and classification is done according to the best match above the operating threshold. In the charts, “Max” stands for the maximum correct recognition rate and “EER” for the Equal-Error-Rate.

Biometric Modalities

The performance results from the palmprint and combined finger surfaces modalities are compared in Table 4-2, along with comparison also against the fusion at score level of the palmprint and finger surfaces. Shown in the table are the best results for each modality for all combinations of operating parameters.

<table>
<thead>
<tr>
<th></th>
<th>Palmprint</th>
<th>Finger Surface</th>
<th>Palmprint + Fingers Fusion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Max</td>
<td>EER</td>
<td>Max</td>
</tr>
<tr>
<td>Zagreb</td>
<td>93.8%</td>
<td>3.1%</td>
<td>100%</td>
</tr>
<tr>
<td>IST</td>
<td>88.6%</td>
<td>8.0</td>
<td>97.7%</td>
</tr>
<tr>
<td>LasPalmas</td>
<td>100.0%</td>
<td>0.0%</td>
<td>100.0%</td>
</tr>
<tr>
<td>UST</td>
<td>95.7%</td>
<td>2.6%</td>
<td>97.9%</td>
</tr>
</tbody>
</table>

It is noticeable that for occasions where the finger surfaces results are already very high, adding the information provided by the palmprint causes no improvement in the
system, meaning that the palmprint modality also fails for those cases where the finger surfaces fail.

However, for those cases where the individual biometric modalities underperform, as happens for very small sized ROIs (4x4 for the palmprint and 4x1 for the finger surfaces), the fusion of both modalities outputs improved performance results that tend to be very high for all tested ROI sizes, as is illustrated in Figure 4-8, for the “UST” database using the LDA algorithm. In the figure, a 4x4 ROI size for the palmprint corresponds to a 4x1 ROI size for the finger surfaces, and so on for larger sizes.

![Figure 4-8 – Performance rate for fusion of modalities.](image)

The operating parameters for the best result in the “UST” database, produce the FAR and FRR curves illustrated in Figure 4-9.

![Figure 4-9 – FAR and FRR curves according to operating threshold.](image)
By raising or lowering the operating system’s threshold, it is possible to obtain a system for which the FAR/FRR is higher or lower according to what is required for the system’s application.

From the tests run for the fusion of the palmprint data with the finger surfaces, it is visible that the sum rule is the one that is most consistent in providing the highest results, while the max rule seems to be the worst. As for the three normalization methods tested, there doesn’t seem to be much of a difference in results between all of them. These results are presented for each database in tables A-9, A-18, A-27 and A-31.

**PCA vs. LDA vs. PCA-LDA**

It is noticeable from the results obtained across all databases that PCA typically yields better results for smaller database sizes, whereas LDA performs better on databases that have a large number of users, as is illustrated in Table 4-3 – shown are the best top results for any ROI size for the palmprint biometric. Even though it is not visible in the table, for the “IST” database, even if LDA has a better top result by a couple of percentage points, PCA is the most consistent across all tests and clearly performs better than LDA for that database.

<table>
<thead>
<tr>
<th>Database</th>
<th>PCA</th>
<th>LDA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Max</td>
<td>FAR</td>
</tr>
<tr>
<td>Zagreb</td>
<td>93.8%</td>
<td>0.0%</td>
</tr>
<tr>
<td>IST</td>
<td>86.4%</td>
<td>11.4%</td>
</tr>
<tr>
<td>LasPalmas</td>
<td>99.2%</td>
<td>0.8%</td>
</tr>
<tr>
<td>UST</td>
<td>85.2%</td>
<td>14.4%</td>
</tr>
</tbody>
</table>

This is because of the well known small sample size problem, which also causes instability problems for the LDA algorithm. A striking case of LDA instability appears for the “UST” database, as illustrated in Table 4-4.

<table>
<thead>
<tr>
<th>Template size</th>
<th>Distance measure</th>
<th>LDA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Max</td>
<td>FAR</td>
</tr>
<tr>
<td>Palmprint</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4x4</td>
<td>84.1%</td>
<td>15.8%</td>
</tr>
<tr>
<td>8x8</td>
<td>95.1%</td>
<td>4.1%</td>
</tr>
<tr>
<td>16x16</td>
<td>95.7%</td>
<td>4.1%</td>
</tr>
<tr>
<td>32x32</td>
<td>88.9%</td>
<td>10.5%</td>
</tr>
<tr>
<td>64x64</td>
<td>2.1%</td>
<td>15%</td>
</tr>
</tbody>
</table>
The solution for this problem is to use the combined PCA-LDA method described in chapter three, which, for the same case and operating parameters, results in a maximum recognition rate of 94.2% and EER equal to 3.6% for a ROI of 64x64 pixels. The complete results for the PCA-LDA method are shown in Table 4-5.

<table>
<thead>
<tr>
<th>Template size</th>
<th>Distance measure</th>
<th>PCA-LDA</th>
<th>Max</th>
<th>FAR</th>
<th>FRR</th>
<th>EER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Palmprint</td>
<td>L2</td>
<td>PCA-LDA</td>
<td>81.4%</td>
<td>17.2%</td>
<td>0.2%</td>
<td>11.4%</td>
</tr>
<tr>
<td>4x4</td>
<td>L2</td>
<td>PCA-LDA</td>
<td>95.2%</td>
<td>4.5%</td>
<td>0.2%</td>
<td>3.0%</td>
</tr>
<tr>
<td>8x8</td>
<td>L2</td>
<td>PCA-LDA</td>
<td>95.2%</td>
<td>4.4%</td>
<td>0.4%</td>
<td>3.0%</td>
</tr>
<tr>
<td>16x16</td>
<td>L2</td>
<td>PCA-LDA</td>
<td>94.5%</td>
<td>5.1%</td>
<td>0.4%</td>
<td>3.3%</td>
</tr>
<tr>
<td>32x32</td>
<td>L2</td>
<td>PCA-LDA</td>
<td>94.2%</td>
<td>5.2%</td>
<td>0.6%</td>
<td>3.8%</td>
</tr>
<tr>
<td>64x64</td>
<td>L2</td>
<td>PCA-LDA</td>
<td>94.2%</td>
<td>5.2%</td>
<td>0.6%</td>
<td>3.8%</td>
</tr>
</tbody>
</table>

**Individual Finger Results**

Individual fingers can perform quite well on their own, as illustrated in Figure 4-10. The given example is for the “UST” database, using the LDA algorithm combined with Euclidean distance and 16x4 finger ROIs. Generally, the performance for the thumb surface is the lowest from all the finger surfaces, as happens in this particular example. This result is as expected and in conformity with other literature [9]. Users usually place the thumb finger in a tilted position, therefore the finger surface features are not captured as well as for the other fingers.
**Fingers Score Level Fusion**

The score level fusion of the individual finger surface scores into a single biometric greatly improves recognition rates, as is illustrated in Figure 4-11. In this example, despite individual finger maximum correct recognition rates being very low (~40%), after mean score fusion the recognition rate reaches 98.8% and the EER is only 1.2%.

![Figure 4-11 – Chart comparing finger surface performance rates.](image)

Tests for the above example were run on the “LasPalmas” database, having a finger ROI size of only 4x1 pixels and using LDA combined with cosine distance measure. Such a small ROI size on a relatively large database explains the poor performance of the individual fingers, since not enough discriminability is achievable. These results are consistent with results from all other databases.

**Region-Of-Interest Size**

The effect of the ROI size on the system performance, measure by the recognition rate, is best visible in large databases, which require more discriminating information to be present in the extracted features. On small or medium databases, ROI size is not as important, being the results achieved for example on the “Zagreb” database exactly equal for all palmprint ROI sizes (from 4x4 up to 256x256), using PCA and the Manhattan L1 distance measure, more specifically achieving a maximum recognition rate of 93.8% and EER of 3.1%.

A good example of the evolution of performance results according to ROI size is in the “UST” database. Illustrated in Figure 4-12 are the maximum recognition and EER results for the middle finger, using the PCA algorithm together with the Manhattan L1 distance measure.
Distance Measures

From the tests conducted, it resulted that there is not an overall best distance measure. What stands out from the results is that the Manhattan (L1) distance measure invariably outperforms the other two measures for the PCA feature extraction algorithm. However, when LDA is used the measures which achieve best results are the Euclidean and Cosine distances, as shown in Table 4-6 for a representative example from the “LasPalmas” database.

<table>
<thead>
<tr>
<th></th>
<th>PCA</th>
<th></th>
<th>LDA</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Max</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Manhattan (L1)</td>
<td>93,6%</td>
<td>72,7%</td>
<td>85,9%</td>
</tr>
<tr>
<td></td>
<td>Euclidean (L2)</td>
<td>87,6%</td>
<td>85,9%</td>
<td>83,1%</td>
</tr>
<tr>
<td></td>
<td>Cosine</td>
<td>91,2%</td>
<td>93,3%</td>
<td>85,9%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>EER</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Manhattan (L1)</td>
<td>4,4%</td>
<td>15,6%</td>
<td>10,2%</td>
</tr>
<tr>
<td></td>
<td>Euclidean (L2)</td>
<td>8,0%</td>
<td>8,2%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Cosine</td>
<td>6,9%</td>
<td>2,9%</td>
<td></td>
</tr>
</tbody>
</table>

These results are in accordance with what is reported in the literature [54].

Training Set Size

The effect of the training set size in the overall system recognition rates is illustrated in Figure 4-13. The example is related to the “Zagreb” database, which has only 4 images per user, thus the training set size was tested with values of 1, 2 or 3 images. The tests refer to the fusion of the finger surfaces, using the LDA algorithm and Euclidean distance for a 4x1 template size. Complete results are shown in table A-8.
It is clear that an under-sampled training set can induce severe penalties for the recognition performance rates of the biometric system, being this true for all database sizes and both for LDA and PCA.

Figure 4-13 – Performance rates according to training set size.

**Number of Eigenvectors**

Another system operating parameter that can impact the system’s recognition performance rates is the number of eigenvectors used in the PCA and LDA algorithms. As expected, the larger the database, the more eigenvectors contain most of the discriminating information.

The example illustrated in Figure 4-14, shows that above a certain amount, no change is noticeable in the performance rates, since the eigenvectors with lowest corresponding eigenvalues carry with them negligible information. However, not using the information of enough eigenvectors dramatically reduces performance.
The example illustrated above is for the “LasPalmas” database, using the PCA algorithm combined with the Manhattan distance measure and a palmprint ROI size of 4x4 pixels. These results are shown in table A-25.

**Best Match vs. k-Nearest Neighbours**

The results for the k-Nearest Neighbours algorithm are mostly the same as if using the best match classification method. For all databases, the majority of the times the k-Nearest Neighbours algorithm is unable to achieve results for $k > 1$ better than for $k = 1$ (this last being equivalent to the best match). Occasionally though, it produces better or worst results, without a clear pattern arising, as is patent in the example illustrated in Table 4-7, for the “IST” database, using the PCA algorithm along with the Manhattan distance and a palmprint ROI size of 4x4 pixels.

*Table 4-7 – Performance rates according to $k$ value.*

<table>
<thead>
<tr>
<th></th>
<th>Palmprint</th>
<th></th>
<th></th>
<th>Fingers Fusion</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>8</td>
<td>16</td>
<td>32</td>
</tr>
<tr>
<td>Max</td>
<td>6,8%</td>
<td>22,1%</td>
<td>57,4%</td>
<td>83,9%</td>
<td>93,6%</td>
<td>93,6%</td>
</tr>
<tr>
<td>EER</td>
<td>48,7%</td>
<td>45,5%</td>
<td>27,4%</td>
<td>10,8%</td>
<td>4,4%</td>
<td>4,4%</td>
</tr>
</tbody>
</table>

This demonstrates that the k-Nearest Neighbours algorithm brings no advantage over the best match method. It also has the disadvantage of requiring higher computation times due to its complexity in comparison. Complete results for the different databases can be found in tables A-10, A-19 and A-28.
5 Conclusions

This thesis presented a multimodal biometric recognition system based on hand images. From a single image acquired by a sensor (scanner or digital camera), two biometric features are computed: palmprint, and finger surface. Different sensors for each biometric modality are not required, nor does it need specific hand placement. This characteristic makes the system flexible, practical and easy to use.

The systems’ pre-processing stage was able to achieve an FTE rate for conformant images very close to 0%, being this an improvement in regards to previous work [7]. For the example, the “UST” database originated a total FTE of 7.1% in this work, while for Sanches et al. [7] this value was of 8.2%.

The proposed multimodal biometric system has shown that the usage of multiple biometrics improves performance in comparison to systems using a single biometric, therefore increasing the security level. The combined results are better overall than the best of the individual biometric recognition results.

The recognition system achieved 97.9% correct recognition rate and a EER of 1.2% on a large scale database and consistent high rates close or equal to 100% for smaller databases, which shows that this work should be continued and might be considered for high security access control systems.

It was also shown that high recognition results are not specific to databases that use a digital camera, but can also be achieved in ones using a scanner, despite its disadvantages mentioned in chapter 3.1.

The results are in line with the best results reported in the literature for multimodal hand biometric systems – state of the art mentioned in the introduction chapter, which are in the range of ~97% up to almost 100% for several different databases, as illustrated in Figure 5-1, where the range in red comprises all the performance rates achieved in this work for the different databases tested. Nevertheless, and although the overall goals for the multimodal biometric system have been achieved, the resulting performance can still be improved.
Figure 5-1 – State of the art biometric systems’ performance rates.

Another achieved goal was the confirmation that a wide range of system operating parameters (ROI size, number of training samples, number of eigenvectors used) can have an enormous impact in the system’s recognition rate. Several methods and algorithms were also compared in what regards to their contribution to the system’s performance, being noticeable that, for example, PCA and LDA alone have several limitations.

Of note, is also the fact that this systems is able to achieve high recognition rates even for very small ROI sizes, by fusing different modalities. Even a palmprint ROI size of only 4x4 pixels combined with a finger surface ROI size of 4x1 pixels, when fused together are able to achieve recognition results of almost 92% on a large database.

Future work should focus on several main possible improvements over the described multimodal biometric system:

- **Segmentation** – A more robust, accurate and flexible segmentation algorithm should be used, so as to be able to process complex image scenes, without the requirement for a constant background. Skin colour information could be an important segmentation aid, existing the possibility of the usage of algorithms already used and researched for face recognition.

- **At a Distance Hand Detection** – Directly linked to the segmentation improvement described above is the possibility of being able to detect and extract the hand image at a distance. This might cause problems of hand pose relative to the biometric sensor, which must be taken into account.
• **Features Correlation** – The level of correlation between the finger surfaces and also with the palmprint should be studied. This will allow the suppression of redundant information from the system, thus reducing processing times.

• **Biometric Fusion** – There are various types of fusion techniques of which only a few were tested. Comparison of different fusion algorithms should also be studied in more detail, more specifically weighted score level fusion, which would allow final score contribution weights to be attributed to each feature, according to their individual performance rates, thus increasing overall system recognition performance.
Presented here are the performance results showing the maximum recognition rate and respective FAR and FRR rates at the corresponding operating threshold. The EER is also shown. These values correspond to the variation of template size and distance measure across all databases. Results for the “Zagreb” database are shown in tables A1 to A10, while A11 to A19 correspond to the “IST” database. Tables A20 to A28 show results for the “LasPalmas” database and A29 to A31 for the “UST” database.

Empty entries correspond to those cases where the processing memory was insufficient for the required calculations. Also, due to the large processing requirements needed for the “UST” database, because of the high number of users, results are only shown for the best metrics of each algorithm – Manhattan (L1) for PCA and Euclidean (L2) for LDA.

“Zagreb” Database Results

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<th>Distance measure</th>
<th>PCA</th>
<th>LDA</th>
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<td>Max</td>
<td>FAR</td>
<td>FRR</td>
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<tr>
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<td>0%</td>
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<td>93.8%</td>
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NOTE: Results are for k=64 eigenvectors and a training set of 2 images.
Table A-2 – PCA and LDA finger fusion results for Zagreb database.

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<th>PCA EER</th>
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<th>LDA FAR</th>
<th>LDA FRR</th>
<th>LDA EER</th>
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NOTE: Results are for k=64 eigenvectors and a training set of 2 images.
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NOTE: Results are for k=64 eigenvectors and a training set of 2 images.
Table A-4 – PCA and LDA ring finger results for Zagreb database.

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<td>25,0%</td>
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<td>6,3%</td>
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NOTE: Results are for k=64 eigenvectors and a training set of 2 images.
Table A-5 – PCA and LDA middle finger results for Zagreb database.

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<td>Max FAR FRR EER</td>
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<td>62.5% 37.5% 0.0% 25.0%</td>
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</tr>
<tr>
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<tr>
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</tr>
<tr>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1</td>
<td>68.8% 18.8% 12.5% 18.8%</td>
<td>56.3% 37.5% 6.3% 28.1%</td>
<td></td>
</tr>
<tr>
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<td>62.5% 25.0% 12.5% 20.8%</td>
<td>43.8% 50.0% 6.3% 31.3%</td>
<td></td>
</tr>
<tr>
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<td>56.3% 37.5% 6.3% 25.0%</td>
<td></td>
</tr>
<tr>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>75.0% 18.8% 6.3% 18.8%</td>
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</tr>
<tr>
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<td></td>
<td></td>
</tr>
<tr>
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<td>50.0% 43.8% 6.3% 28.1%</td>
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<tr>
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<td>56.3% 37.5% 6.3% 25.0%</td>
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</tr>
<tr>
<td>Cos</td>
<td>81.3% 18.8% 0.0% 18.8%</td>
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</tr>
<tr>
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</tr>
<tr>
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</tr>
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</tr>
<tr>
<td>Cos</td>
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</tr>
<tr>
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<td>- - - -</td>
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</tr>
<tr>
<td>Cos</td>
<td>81.3% 18.8% 0.0% 18.8%</td>
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NOTE: Results are for k=64 eigenvectors and a training set of 2 images.
Table A-6 – PCA and LDA index finger results for Zagreb database.

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<th>LDA</th>
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<td></td>
<td>Max</td>
<td>FAR</td>
</tr>
<tr>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
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<td>31.3%</td>
</tr>
<tr>
<td></td>
<td>L2</td>
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<td>37.5%</td>
</tr>
<tr>
<td></td>
<td>Cos</td>
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<td>31.3%</td>
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<td>L2</td>
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<td>25.0%</td>
</tr>
<tr>
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<td>Cos</td>
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<td>18.8%</td>
</tr>
<tr>
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<td>12.5%</td>
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<td>12.5%</td>
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<td>L2</td>
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<td>Cos</td>
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<td>L2</td>
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<td>12.5%</td>
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<tr>
<td></td>
<td>L2</td>
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<td>12.5%</td>
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<tr>
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<td>Cos</td>
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<td>256x64</td>
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<td>87.5%</td>
<td>12.5%</td>
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<td>L2</td>
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</tr>
<tr>
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<td>Cos</td>
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<td>12.5%</td>
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NOTE: Results are for k=64 eigenvectors and a training set of 2 images.
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<th>LDA</th>
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<tbody>
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<td>Max</td>
<td>FAR</td>
<td>FRR</td>
</tr>
<tr>
<td>Thumb Finger</td>
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<tr>
<td>L1</td>
<td>62,5%</td>
<td>25,0%</td>
<td>12,5%</td>
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<tr>
<td>L2</td>
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<td>37,5%</td>
<td>6,3%</td>
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<tr>
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<td>31,3%</td>
<td>18,8%</td>
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<tr>
<td>8x2</td>
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<td>L1</td>
<td>68,8%</td>
<td>12,5%</td>
<td>18,8%</td>
</tr>
<tr>
<td>L2</td>
<td>68,8%</td>
<td>18,8%</td>
<td>12,5%</td>
</tr>
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<td>12,5%</td>
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<td>12,5%</td>
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<td>25,0%</td>
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<td>18,8%</td>
<td>0,0%</td>
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<tr>
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<td>12,5%</td>
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<tr>
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<td>0,0%</td>
<td>18,8%</td>
</tr>
<tr>
<td>64x16</td>
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<td></td>
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</tr>
<tr>
<td>L1</td>
<td>81,3%</td>
<td>18,8%</td>
<td>0,0%</td>
</tr>
<tr>
<td>L2</td>
<td>75,0%</td>
<td>12,5%</td>
<td>12,5%</td>
</tr>
<tr>
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<td>81,3%</td>
<td>0,0%</td>
<td>18,8%</td>
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<tr>
<td>128x32</td>
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</tr>
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<td>18,8%</td>
<td>0,0%</td>
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<tr>
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<td>18,8%</td>
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NOTE: Results are for k=64 eigenvectors and a training set of 2 images.
Table A-8 – Different trainset size results for Zagreb database.

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<th>LDA</th>
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<td>Trainset size: 1</td>
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<tr>
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<td>62,5%</td>
<td>20,8%</td>
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<td>L1</td>
<td>33,3%</td>
<td>58,3%</td>
</tr>
<tr>
<td>Ring Finger</td>
<td>L1</td>
<td>33,3%</td>
<td>54,2%</td>
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<tr>
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<td>62,5%</td>
</tr>
<tr>
<td>Middle Finger</td>
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<td>33,3%</td>
<td>41,7%</td>
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<tr>
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<td>58,3%</td>
<td>41,7%</td>
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<td></td>
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<td>0,0%</td>
</tr>
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<td>Finger Fusion</td>
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<td>12,5%</td>
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<td>31,3%</td>
</tr>
<tr>
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<td>L1</td>
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<td>37,5%</td>
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<tr>
<td>Index Finger</td>
<td>L1</td>
<td>37,5%</td>
<td>62,5%</td>
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<tr>
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<td>L1</td>
<td>62,5%</td>
<td>31,3%</td>
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<tr>
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<td>L1</td>
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<td>25,0%</td>
</tr>
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<td>0,0%</td>
</tr>
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<td>30,0%</td>
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<td>30,0%</td>
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<td>Thumb Finger</td>
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NOTE: Results are for k=64 eigenvectors, palmprint ROIs of 4x4 and finger ROIs of 4x1.
Table A.9 – Biometric modalities fusion results for Zagreb database.

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<td>Divide by Max</td>
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</tr>
<tr>
<td></td>
<td>Min-Max</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8x8 8x2</td>
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<td>25.0%</td>
</tr>
<tr>
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<td>Max</td>
<td>87.5%</td>
<td>12.5%</td>
</tr>
<tr>
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<td>Max</td>
<td>100.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td></td>
<td>Prod</td>
<td>93.8%</td>
<td>0.0%</td>
</tr>
<tr>
<td></td>
<td>Min-Max</td>
<td></td>
<td></td>
</tr>
<tr>
<td>16x16 16x4</td>
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</tr>
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<td>0.0%</td>
</tr>
<tr>
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<td>Max</td>
<td>93.8%</td>
<td>0.0%</td>
</tr>
<tr>
<td></td>
<td>Prod</td>
<td>93.8%</td>
<td>0.0%</td>
</tr>
<tr>
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<td>Min-Max</td>
<td></td>
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</tr>
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<td>0.0%</td>
</tr>
<tr>
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<td>Prod</td>
<td>93.8%</td>
<td>0.0%</td>
</tr>
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<td>Min-Max</td>
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</tr>
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<td>Max</td>
<td>93.8%</td>
<td>0.0%</td>
</tr>
<tr>
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<td>Prod</td>
<td>93.8%</td>
<td>0.0%</td>
</tr>
<tr>
<td></td>
<td>Min-Max</td>
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</tbody>
</table>

NOTE: Results are for k=64 eigenvectors and a training set of 2 images.
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<th>LDA</th>
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</tr>
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<td>FAR</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>FRR</td>
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</tr>
<tr>
<td></td>
<td></td>
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**Table A-10 – k-Nearest Neighbours results for Zagreb database.**

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<th>LDA</th>
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<td>Max</td>
<td>FAR</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PCA</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>FAR</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>FRR</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EER</td>
<td>3%</td>
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</tbody>
</table>

**NOTE:** Results are for k=64 eigenvectors, palmprint ROIs of 4x4, finger ROIs of 4x1 and a training set of 2 images.
## “IST” Database Results

Table A-11 – PCA and LDA palmprint results for IST database.

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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>FAR</td>
<td>FRR</td>
<td>EER</td>
<td>FAR</td>
<td>FRR</td>
<td>EER</td>
<td>FAR</td>
<td>FRR</td>
<td>EER</td>
<td>FAR</td>
</tr>
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<td>11.4%</td>
<td>88.6%</td>
<td>11.4%</td>
<td>0%</td>
<td>8.0%</td>
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<td>17.1%</td>
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<td>11.4%</td>
<td>0%</td>
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<td></td>
<td></td>
</tr>
<tr>
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<td>18.2%</td>
<td>0%</td>
<td>15.9%</td>
<td>88.6%</td>
<td>11.4%</td>
<td>0%</td>
<td>10.2%</td>
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</tr>
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<td>29.5%</td>
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<td>4.5%</td>
<td>38.6%</td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>L2</td>
<td>79.5%</td>
<td>20.5%</td>
<td>0%</td>
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NOTE: Results are for k=64 eigenvectors and a training set of 5 images.
Table A-12 – PCA and LDA finger fusion results for IST database.

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NOTE: Results are for k=64 eigenvectors and a training set of 5 images.
Table A-13 – PCA and LDA pinkie finger results for IST database.

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NOTE: Results are for k=64 eigenvectors and a training set of 5 images.
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NOTE: Results are for k=64 eigenvectors and a training set of 5 images.
Table A-15 – PCA and LDA middle finger results for IST database.

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NOTE: Results are for k=64 eigenvectors and a training set of 5 images.
Table A-16 – PCA and LDA index finger results for IST database.

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<td>Cos</td>
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NOTE: Results are for k=64 eigenvectors and a training set of 5 images.
Table A-17 – PCA and LDA thumb finger results for IST database.

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<td>FRR</td>
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<tr>
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NOTE: Results are for k=64 eigenvectors and a training set of 5 images.
Table A-18 – Biometric modalities fusion results for IST database.

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<td>Min-Max</td>
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<td>2.3%</td>
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NOTE: Results are for k=64 eigenvectors and a training set of 5 images.
Table A-19 – k-Nearest Neighbours results for IST database.

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<td>18,2%</td>
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<td>15,9%</td>
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NOTE: Results are for k=64 eigenvectors, palmprint ROIs of 4x4, finger ROIs of 4x1 and a training set of 5 images.
“LasPalmas” Database Results

Table A-20 – PCA and LDA palmprint results for LasPalmas database.

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NOTE: Results are for k=64 eigenvectors and a training set of 5 images.
### Table A-21 – PCA and LDA finger fusion results for LasPalmas database.

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**NOTE:** Results are for k=64 eigenvectors and a training set of 5 images.
Table A-22 – PCA and LDA pinkie and ring fingers results for LasPalmas database.

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NOTE: Results are for k=64 eigenvectors and a training set of 5 images.
## Table A-23 – PCA and LDA middle and index fingers results for LasPalmas database.

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**NOTE:** Results are for k=64 eigenvectors and a training set of 5 images.
### Table A-24 – PCA and LDA thumb finger results for LasPalmas database.

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<tr>
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<td>Cos</td>
<td>85.1%</td>
<td>14.9%</td>
</tr>
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<td>16x4</td>
<td>L1</td>
<td>97.2%</td>
<td>0.8%</td>
</tr>
<tr>
<td></td>
<td>L2</td>
<td>95.6%</td>
<td>2.8%</td>
</tr>
<tr>
<td></td>
<td>Cos</td>
<td>94.4%</td>
<td>5.2%</td>
</tr>
<tr>
<td>32x8</td>
<td>L1</td>
<td>97.6%</td>
<td>0.8%</td>
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<tr>
<td></td>
<td>L2</td>
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<td>2.0%</td>
</tr>
<tr>
<td></td>
<td>Cos</td>
<td>95.2%</td>
<td>4.8%</td>
</tr>
<tr>
<td>64x16</td>
<td>L1</td>
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<td>2.4%</td>
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<td>L2</td>
<td>95.2%</td>
<td>4.4%</td>
</tr>
<tr>
<td></td>
<td>Cos</td>
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<td>5.2%</td>
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<td>128x32</td>
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<td>96.8%</td>
<td>3.2%</td>
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<tr>
<td></td>
<td>L2</td>
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<td>4.0%</td>
</tr>
<tr>
<td></td>
<td>Cos</td>
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</tr>
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</table>

NOTE: Results are for k=64 eigenvectors and a training set of 5 images.
Table A-25 – Different number of eigenvalues results for LasPalmas database.

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<thead>
<tr>
<th>Feature</th>
<th>Distance measure</th>
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<th>Distance measure</th>
<th>LDA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Max</td>
<td>FAR</td>
<td>FRR</td>
</tr>
<tr>
<td>Palmprint</td>
<td>L1</td>
<td>6,8%</td>
<td>93,2%</td>
<td>0,0%</td>
</tr>
<tr>
<td>Finger Fusion</td>
<td>L1</td>
<td>55,8%</td>
<td>44,2%</td>
<td>0,0%</td>
</tr>
<tr>
<td>Pinkie Finger</td>
<td>L1</td>
<td>4,8%</td>
<td>95,2%</td>
<td>0,0%</td>
</tr>
<tr>
<td>Ring Finger</td>
<td>L1</td>
<td>10,0%</td>
<td>90,0%</td>
<td>0,0%</td>
</tr>
<tr>
<td>Index Finger</td>
<td>L1</td>
<td>7,2%</td>
<td>92,8%</td>
<td>0,0%</td>
</tr>
<tr>
<td>Middle Finger</td>
<td>L1</td>
<td>6,8%</td>
<td>92,8%</td>
<td>0,4%</td>
</tr>
<tr>
<td>Thumb Finger</td>
<td>L1</td>
<td>11,6%</td>
<td>88,3%</td>
<td>0,0%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Palmprint</td>
<td>L1</td>
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<td>77,5%</td>
<td>0,4%</td>
</tr>
<tr>
<td>Finger Fusion</td>
<td>L1</td>
<td>83,5%</td>
<td>16,5%</td>
<td>0,0%</td>
</tr>
<tr>
<td>Pinkie Finger</td>
<td>L1</td>
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<td>75,5%</td>
<td>0,0%</td>
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<tr>
<td>Ring Finger</td>
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<td>77,5%</td>
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</tr>
<tr>
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<td>80,3%</td>
<td>0,8%</td>
</tr>
<tr>
<td>Middle Finger</td>
<td>L1</td>
<td>15,7%</td>
<td>84,3%</td>
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</tr>
<tr>
<td>Thumb Finger</td>
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<td>25,7%</td>
<td>74,3%</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Palmprint</td>
<td>L1</td>
<td>57,4%</td>
<td>42,6%</td>
<td>0,0%</td>
</tr>
<tr>
<td>Finger Fusion</td>
<td>L1</td>
<td>92,8%</td>
<td>6,8%</td>
<td>0,4%</td>
</tr>
<tr>
<td>Pinkie Finger</td>
<td>L1</td>
<td>49,8%</td>
<td>49,8%</td>
<td>0,4%</td>
</tr>
<tr>
<td>Ring Finger</td>
<td>L1</td>
<td>55,0%</td>
<td>44,2%</td>
<td>0,8%</td>
</tr>
<tr>
<td>Index Finger</td>
<td>L1</td>
<td>50,6%</td>
<td>48,6%</td>
<td>0,8%</td>
</tr>
<tr>
<td>Middle Finger</td>
<td>L1</td>
<td>43,8%</td>
<td>56,2%</td>
<td>0,0%</td>
</tr>
<tr>
<td>Thumb Finger</td>
<td>L1</td>
<td>48,2%</td>
<td>51,4%</td>
<td>0,4%</td>
</tr>
</tbody>
</table>

NOTE: Results are for palmprint ROIs of 4x4, finger ROIs of 4x1 and a training set of 5 images.
Table A.26 – Different number of eigenvalues results for LasPalmas database (cont.).

<table>
<thead>
<tr>
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<th>Distance measure</th>
<th>PCA</th>
<th>LDA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Max</td>
<td>FAR</td>
</tr>
<tr>
<td></td>
<td></td>
<td>L1</td>
<td>L2</td>
</tr>
<tr>
<td># eigenvalues: 8</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Palmprint</td>
<td>L1</td>
<td>83,9%</td>
<td>15,3%</td>
</tr>
<tr>
<td>Finger Fusion</td>
<td>L1</td>
<td>92,8%</td>
<td>6,8%</td>
</tr>
<tr>
<td>Pinkie Finger</td>
<td>L1</td>
<td>49,8%</td>
<td>49,8%</td>
</tr>
<tr>
<td>Ring Finger</td>
<td>L1</td>
<td>55,0%</td>
<td>44,2%</td>
</tr>
<tr>
<td>Index Finger</td>
<td>L1</td>
<td>50,6%</td>
<td>48,6%</td>
</tr>
<tr>
<td>Middle Finger</td>
<td>L1</td>
<td>43,8%</td>
<td>56,2%</td>
</tr>
<tr>
<td>Thumb Finger</td>
<td>L1</td>
<td>48,2%</td>
<td>51,4%</td>
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</tbody>
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# eigenvalues: 16

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<th>LDA</th>
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<tbody>
<tr>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Palmprint</td>
<td>L1</td>
<td>93,6%</td>
<td>6,4%</td>
</tr>
<tr>
<td>Finger Fusion</td>
<td>L1</td>
<td>92,8%</td>
<td>6,8%</td>
</tr>
<tr>
<td>Pinkie Finger</td>
<td>L1</td>
<td>49,8%</td>
<td>49,8%</td>
</tr>
<tr>
<td>Ring Finger</td>
<td>L1</td>
<td>55,0%</td>
<td>44,2%</td>
</tr>
<tr>
<td>Index Finger</td>
<td>L1</td>
<td>50,6%</td>
<td>48,6%</td>
</tr>
<tr>
<td>Middle Finger</td>
<td>L1</td>
<td>43,8%</td>
<td>56,2%</td>
</tr>
<tr>
<td>Thumb Finger</td>
<td>L1</td>
<td>48,2%</td>
<td>51,4%</td>
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</table>

# eigenvalues: 32

<table>
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<th>LDA</th>
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<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Palmprint</td>
<td>L1</td>
<td>93,6%</td>
<td>6,4%</td>
</tr>
<tr>
<td>Finger Fusion</td>
<td>L1</td>
<td>92,8%</td>
<td>6,8%</td>
</tr>
<tr>
<td>Pinkie Finger</td>
<td>L1</td>
<td>49,8%</td>
<td>49,8%</td>
</tr>
<tr>
<td>Ring Finger</td>
<td>L1</td>
<td>55,0%</td>
<td>44,2%</td>
</tr>
<tr>
<td>Index Finger</td>
<td>L1</td>
<td>50,6%</td>
<td>48,6%</td>
</tr>
<tr>
<td>Middle Finger</td>
<td>L1</td>
<td>43,8%</td>
<td>56,2%</td>
</tr>
<tr>
<td>Thumb Finger</td>
<td>L1</td>
<td>48,2%</td>
<td>51,4%</td>
</tr>
</tbody>
</table>

NOTE: Results are for palmprint ROIs of 4x4, finger ROIs of 4x1 and a training set of 5 images.
Table A-27 – Biometric modalities fusion results for LasPalmas database.

<table>
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<tr>
<td></td>
<td></td>
<td>Max</td>
<td>FAR</td>
</tr>
<tr>
<td></td>
<td>Divide by Max</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4x4 4x1</td>
<td>Sum</td>
<td>98.0%</td>
<td>2.0%</td>
</tr>
<tr>
<td></td>
<td>Min-Max</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8x8 8x2</td>
<td>Sum</td>
<td>99.6%</td>
<td>0.4%</td>
</tr>
<tr>
<td></td>
<td>Min-Max</td>
<td></td>
<td></td>
</tr>
<tr>
<td>16x16 16x4</td>
<td>Sum</td>
<td>100.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td></td>
<td>Min-Max</td>
<td></td>
<td></td>
</tr>
<tr>
<td>32x32 32x8</td>
<td>Sum</td>
<td>100.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td></td>
<td>Min-Max</td>
<td></td>
<td></td>
</tr>
<tr>
<td>64x64 64x16</td>
<td>Sum</td>
<td>100.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td></td>
<td>Min-Max</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

NOTE: Results are for k=64 eigenvectors and a training set of 5 images.
<table>
<thead>
<tr>
<th>Feature</th>
<th>Distance measure</th>
<th>PCA</th>
<th>LDA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Max</td>
<td>FAR</td>
<td>FRR</td>
</tr>
<tr>
<td>k-NN: 1</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Palmprint</td>
<td>L1</td>
<td>93,6%</td>
<td>6,4%</td>
</tr>
<tr>
<td>Finger Fusion</td>
<td>L1</td>
<td>92,8%</td>
<td>6,8%</td>
</tr>
<tr>
<td>k-NN: 3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Palmprint</td>
<td>L1</td>
<td>90,8%</td>
<td>9,2%</td>
</tr>
<tr>
<td>Finger Fusion</td>
<td>L1</td>
<td>91,6%</td>
<td>8,0%</td>
</tr>
<tr>
<td>k-NN: 5</td>
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<td></td>
</tr>
<tr>
<td>Palmprint</td>
<td>L1</td>
<td>91,2%</td>
<td>8,8%</td>
</tr>
<tr>
<td>Finger Fusion</td>
<td>L1</td>
<td>92,0%</td>
<td>7,6%</td>
</tr>
</tbody>
</table>

NOTE: Results are for palmprint ROIs of 4x4, finger ROIs of 4x1 and a training set of 5 images.
## “UST” Database Results

Table A-29 – PCA and LDA palmprint and finger fusion results for UST database.

<table>
<thead>
<tr>
<th>Template size</th>
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<th>LDA</th>
<th>PCA</th>
<th>LDA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Max FAR FRR EER</td>
<td>Max FAR FRR EER</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PCA</td>
<td>LDA</td>
<td>LDA</td>
<td>L2</td>
<td>L2</td>
</tr>
<tr>
<td>4x4</td>
<td>L1 59.2% 40.8% 0.1% 23.6%</td>
<td>L2 84.1% 15.8% 0.1% 10.5%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8x8</td>
<td>L1 82.2% 17.6% 0.2% 10.9%</td>
<td>L2 95.1% 4.1% 0.8% 3%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>16x16</td>
<td>L1 85.2% 14.4% 0.3% 9.1%</td>
<td>L2 95.7% 4.1% 0.3% 2.6%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>32x32</td>
<td>L1 84.7% 15.1% 0.2% 9.4%</td>
<td>L2 88.9% 10.5% 0.6% 6.8%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>64x64</td>
<td>L1 84.4% 15.4% 0.2% 9.7%</td>
<td>L2 2.1% 15% 82.0% 49.2%</td>
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<td></td>
<td></td>
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</tbody>
</table>

**Finger Fusion**

<table>
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<th>LDA</th>
<th>PCA</th>
<th>LDA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Max FAR FRR EER</td>
<td>Max FAR FRR EER</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4x1</td>
<td>L1 63.1% 36.9% 0.1% 22.2%</td>
<td>L2 65.0% 34.7% 0.3% 23.1%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8x2</td>
<td>L1 87.2% 12.6% 0.2% 7.9%</td>
<td>L2 96.8% 3.1% 0% 2.3%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>16x4</td>
<td>L1 94.1% 5.7% 0.2% 4%</td>
<td>L2 97.9% 2.1% 0% 1.2%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>32x8</td>
<td>L1 95% 5% 0% 3.6%</td>
<td>L2 97.9% 2.1% 0% 1.4%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>64x16</td>
<td>L1 94.9% 5% 0.1% 3.8%</td>
<td>L2 96.82% 3.1% 0% 2.5%</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

**NOTE:** Results are for k=64 eigenvectors and a training set of 5 images.
Table A-30 – PCA and LDA finger results for UST database.

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<th></th>
<th></th>
<th>Distance measure</th>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
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<td>Max</td>
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</tr>
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<td>4x1</td>
<td>L1</td>
<td>13.5</td>
<td>86.5%</td>
<td>0.0%</td>
<td>46.7%</td>
<td>L2</td>
<td>18.8%</td>
<td>81.1%</td>
<td>0.1%</td>
</tr>
<tr>
<td>8x2</td>
<td>L1</td>
<td>57.8</td>
<td>42.0%</td>
<td>0.2%</td>
<td>25.1%</td>
<td>L2</td>
<td>82%</td>
<td>17.9%</td>
<td>0.1%</td>
</tr>
<tr>
<td>16x4</td>
<td>L1</td>
<td>81.0</td>
<td>19.0%</td>
<td>0.0%</td>
<td>11.6%</td>
<td>L2</td>
<td>93.8%</td>
<td>6.1%</td>
<td>0.2%</td>
</tr>
<tr>
<td>32x8</td>
<td>L1</td>
<td>82.3</td>
<td>17.7%</td>
<td>0.0%</td>
<td>10.8%</td>
<td>L2</td>
<td>91.9%</td>
<td>7.8%</td>
<td>0.3%</td>
</tr>
<tr>
<td>64x16</td>
<td>L1</td>
<td>81.0</td>
<td>19.0%</td>
<td>0.0%</td>
<td>11.5%</td>
<td>L2</td>
<td>80.3%</td>
<td>19.7%</td>
<td>0%</td>
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</tbody>
</table>

**Pinkie Finger**

<table>
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<th></th>
<th></th>
<th>Distance measure</th>
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<th></th>
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<td>87.4%</td>
<td>0.1%</td>
<td>46.7%</td>
<td>L2</td>
<td>17.8%</td>
<td>82.2%</td>
<td>0.0%</td>
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<td>44.7%</td>
<td>0.2%</td>
<td>25.9%</td>
<td>L2</td>
<td>86.4%</td>
<td>13.4%</td>
<td>0.2%</td>
</tr>
<tr>
<td>16x4</td>
<td>L1</td>
<td>83.6</td>
<td>16.2%</td>
<td>0.2%</td>
<td>10%</td>
<td>L2</td>
<td>96.1%</td>
<td>3.8%</td>
<td>0.1%</td>
</tr>
<tr>
<td>32x8</td>
<td>L1</td>
<td>86.1</td>
<td>13.8%</td>
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<td>95%</td>
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<td>L2</td>
<td>88.8%</td>
<td>11.1%</td>
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</table>

**Ring Finger**

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<th></th>
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<td>46.6%</td>
<td>L2</td>
<td>18.7%</td>
<td>81.3%</td>
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<td>8x2</td>
<td>L1</td>
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<td>44%</td>
<td>0.2%</td>
<td>25.9%</td>
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<td>86.8%</td>
<td>12.9%</td>
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</tr>
<tr>
<td>16x4</td>
<td>L1</td>
<td>83.9</td>
<td>16%</td>
<td>0%</td>
<td>9.9%</td>
<td>L2</td>
<td>96.9%</td>
<td>3%</td>
<td>0.1%</td>
</tr>
<tr>
<td>32x8</td>
<td>L1</td>
<td>87.1</td>
<td>12.7%</td>
<td>0.1%</td>
<td>8%</td>
<td>L2</td>
<td>96.2%</td>
<td>3.6%</td>
<td>0.2%</td>
</tr>
<tr>
<td>64x16</td>
<td>L1</td>
<td>87.4</td>
<td>12%</td>
<td>0%</td>
<td>8%</td>
<td>L2</td>
<td>90.3%</td>
<td>9.7%</td>
<td>0%</td>
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</table>

**Middle Finger**

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<td>46.6%</td>
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<td>18.8%</td>
<td>81.1%</td>
<td>0.0%</td>
</tr>
<tr>
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<td>L1</td>
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<td>L2</td>
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<td>82%</td>
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<td>4.5%</td>
<td>0%</td>
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<tr>
<td>32x8</td>
<td>L1</td>
<td>84.1</td>
<td>15.9%</td>
<td>0%</td>
<td>9.8%</td>
<td>L2</td>
<td>94.3%</td>
<td>5.7%</td>
<td>0%</td>
</tr>
<tr>
<td>64x16</td>
<td>L1</td>
<td>83.3</td>
<td>16.7%</td>
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<td>10.3%</td>
<td>L2</td>
<td>83.5%</td>
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**Index Finger**

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<td>0.2%</td>
<td>45.3%</td>
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<td>75.7%</td>
<td>0%</td>
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<td>L1</td>
<td>57.3</td>
<td>42.6%</td>
<td>0.1%</td>
<td>25.7%</td>
<td>L2</td>
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<td>26.9%</td>
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<td>L2</td>
<td>83.5%</td>
<td>16.4%</td>
<td>0.1%</td>
</tr>
<tr>
<td>32x8</td>
<td>L1</td>
<td>75.4</td>
<td>24.4%</td>
<td>0.2%</td>
<td>15.4%</td>
<td>L2</td>
<td>81%</td>
<td>18.8%</td>
<td>0.2%</td>
</tr>
<tr>
<td>64x16</td>
<td>L1</td>
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<td>0%</td>
<td>15.6%</td>
<td>L2</td>
<td>57.7%</td>
<td>42.3%</td>
<td>0%</td>
</tr>
</tbody>
</table>

**Thumb Finger**

NOTE: Results are for k=64 eigenvectors and a training set of 5 images.
### Table A-31 – Biometrics modalities fusion results for UST database.

<table>
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<tr>
<th>Template size</th>
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<th>EER</th>
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<tr>
<td>8x8</td>
<td>Sum</td>
<td>Min-Max</td>
<td>97,3%</td>
<td>2,6%</td>
<td>0,1%</td>
</tr>
<tr>
<td>16x16</td>
<td>Sum</td>
<td>Min-Max</td>
<td>97,9%</td>
<td>2,1%</td>
<td>0,0%</td>
</tr>
<tr>
<td>32x32</td>
<td>Sum</td>
<td>Min-Max</td>
<td>97,5%</td>
<td>2,4%</td>
<td>0,2%</td>
</tr>
<tr>
<td>64x64</td>
<td>Sum</td>
<td>Min-Max</td>
<td>96,8%</td>
<td>3,1%</td>
<td>0,0%</td>
</tr>
</tbody>
</table>

NOTE: Results are for k=64 eigenvectors and a training set of 5 images.
References


[51] UST Hand Image Database, Department of Computer Science, The Hong Kong University of Science and Technology. (Provided by Dr. Helen Shen)

[52] Departamento de Señales y Comunicaciones, University of Las Palmas (http://www.gpds.ulpge.es/download/index.htm)
