Embedding Local Quality Measures in Minutiae-Based Biometric Recognition

THÈSE N^{O} 7035 (2016)

PRÉSENTÉE LE 7 OCTOBRE 2016

À LA FACULTÉ DES SCIENCES ET TECHNIQUES DE L'INGÉNIEUR
LABORATOIRE DE TRAITEMENT DES SIGNAUX 5
PROGRAMME DOCTORAL EN GÉNIE ÉLECTRIQUE

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

POUR L'OBTENTION DU GRADE DE DOCTEUR ÈS SCIENCES

PAR

Mohammad Hamed IZADI

acceptée sur proposition du jury:

Prof. P. Fua, président du jury
Dr A. Drygajlo, directeur de thèse
Prof. C. Champod, rapporteur
Prof. R. Veldhuis, rapporteur
Dr J.-M. Vesin, rapporteur

ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Suisse
2016

We can only see a short distance ahead, but
we can see plenty there that needs to be done.
— Alan Turing

To my parents...

Acknowledgements

First and foremost, I owe my great gratitude to my thesis director, Dr. Andrzej Drygajlo, for providing me the special opportunity to work on this thesis. Without his guidance and extreme patience, it was indeed impossible to reach the current point of success.

I would like also to thank my thesis jury members Prof. Raymond Veldhuis, Prof. Christophe Champod, Dr. Jean-Marc Vesin, and Prof. Pascal Fua for having accepted to review my thesis and for helpful feedback and suggestions.

I am also thankful to Prof. Jean-Philippe Thiran for supporting me during some periods before and after my doctoral studies. His warm attitude towards others has been always inspiring.

I am very grateful to the members of our group, Leila, Finnian, Rudolf, and all other members of the Signal Processing Labs at EPFL, especially Christina, Maryna, Saeed, Raphael, Sasan, Sybille, Marina, Vijay, Murat, Ashkan, Maryna, Mahdad, and Momo for all enjoying time and memories we shared during the past several years. Special thanks to Leila for the collaborations we had at the beginning of this work.

I would like to extend my thanks to the BioLab members at the University of Bologna, especially Prof. Raffaele Cappelli and Dr. Matteo Ferrara for hosting me in their group with a great support and for the fruitful discussions we had. This period was indeed very beneficial in the course of my PhD research.

I am also thankful to Swiss National science Foundation (SNSF) and Swiss State Secretariat for Education, Research and Innovation (SEFRI) for supporting my research during these years.

I am so grateful to many great friends whom I have been fortunate to meet and share enjoyable moments with during the course of this thesis in Lausanne; Particularly, I would like to thank Kamran Kalbasi, Mehdi Alem (aka Ostad), Mobasher Niqui, Mohammad Golbabaee, Mahdad Hosseini Kamal, Mohsen Cheraghi, Maryna and Sebastien Waszak, Seyed Ali Reza Mousavi, Hamed Hassani, Masoud Alipour, Alice Moscardi, and Armand Vedadi. Big thanks to Kamran for the open-ended discussions and enormous laughs that I never forget.

I also want to express my sincere gratitude to Catherine for her true friendship, care and encouragement especially during the final period of this thesis.

Finally, I am greatly thankful to my brother, Hadi, and my sister, Leila, for their love and support.

Last but not least, I would like to deeply thank my parents, Hayedeh and Mojtaba, for all their support, care and love throughout my life. To them I dedicate this thesis.

Lausanne, May 2016 Hamed Izadi

Abstract

Degradation in data quality is still a main source of errors in the modern biometric recognition systems. However, the data quality can be embedded in the recognition methods at global and local levels to build more accurate biometric systems. Local quality measures represent the quality of local parts within a biometric sample. They are either combined into a global quality measure or directly embedded into the recognition techniques. Minutiae-based comparison is the main and the most common technique used for fingerprint recognition and high-resolution palmprint recognition in various security and forensic applications. The focus of this thesis is mainly on direct incorporation of the local quality measures into the state-of-the-art minutiae-based recognition methods, particularly those based on Minutiae Cylinder-Code (MCC). Firstly, we introduce cylinder quality measures as a new type of local quality measures associated with the local minutiae descriptors. Then, we propose several methods for incorporating such local quality measures into the biometric systems, in order to improve their recognition performance. Among them is a novel and efficient quality-based consolidation method for embedding minutiae quality and cylinder quality measures in MCC based comparison methods. We also propose a supervised embedding method based on a binary classification model, which requires labeled minutiae for training. Finally, we apply a variant of the proposed consolidation method for the challenging case of latent fingerprint and palmprint identification with embedded subjective and objective minutiae quality.

Key words: biometric recognition, data quality, local quality measure, fingerprint, palmprint, latent print, minutia, minutiae-based matching, local minutiae descriptor, Minutia Cylinder-Code

Résumé

La dégradation de la qualité des données est toujours une source principale d'erreurs au sein des systèmes de reconnaissance biométrique moderne. Cependant, la qualité des données peut être intégrée dans des méthodes de reconnaissance aux nivaux globales et locales afin de construire des systèmes biométriques plus précis. Des mesures locales de qualité représentent la qualité des pièces locales dans un échantillon biométrique. Ils sont soit combinés en une mesure globale de la qualité ou directement intégrés dans les techniques de reconnaissance. Une comparaison basée sur les minuties est la technique principale la plus courante pour la reconnaissance d'empreintes digitales et empreintes de la paume en haute résolution dans diverses applications sécuritaires et forensiques. L'objectif de cette thèse porte principalement sur l'incorporation directe des mesures locales de qualité au sein des méthodes de reconnaissance les plus récentes basées sur la minutie, et particulièrement basées sur le Minutia Cylinder-Code (MCC). Premièrement, nous débuterons par les mesures de qualité du Cylindre en tant que nouveau type de mesures de qualité locales associées aux descripteurs de minuties locaux. Puis, nous proposons plusieurs méthodes pour incorporer lesdites mesures de qualité locale dans les systèmes biométriques afin d'améliorer leur performance de reconnaissance. Cette action offre une nouvelle méthode de consolidation efficace basée sur la qualité pour intégrer la qualité des minuties ainsi que les mesures de qualité du Cylindre basée sur les méthodes comparatives. Nous proposons également une méthode d'intégration supervisée basée sur le modèle de classification binaire, nécessitant une base de données déjà classifiée pour entraînement. Finalement, nous appliquerons une variante de la méthode de consolidation proposée pour le cas difficile d'empreintes digitales latentes avec la qualité subjective et objective des minuties intégrée.

Mots clefs : reconnaissance biométrique, qualité des données, mesures locales de qualité, empreinte digitale, empreinte de la paume, empreinte latente, minutie, appariement de minuties, descripteur de minuties locaux, Minutia Cylinder-Code

Contents

List of Figures

List of Tables

1 Introduction

Biometric recognition of persons has been widely incorporated in modern life for security and forensic applications [64]. Automated biometric recognition systems began to develop more than 50 years ago using fingerprints [103], however degradation in biometric data quality is still a main source of errors in the state-of-the-art biometric systems [65].

The pattern of ridges existing on the skin of hand palm and fingers is shown to be a reliable trait for biometric recognition [8, 84]. Fingerprint and palmprint are two well-known examples of this kind. Minutiae, which are mainly determined by the terminations and bifurcations of the ridges, are known as the most discriminating features of such ridge patterns. Minutiae, including their position and direction, are also the main and most widely used features for fingerprint and forensic palmprint recognition. Minutiae-based biometric recognition methods are generally based on either global or local minutiae comparison (aka matching[1]). Global minutiae comparison is normally based on finding correspondences between two sets of minutiae after some global alignments. Global comparison methods have some weaknesses such as need for precise alignments and lack of robustness to nonlinear distortions and local degradations. The local minutiae comparison techniques have been proposed in order to address such weaknesses [84]. In this type of methods, minutiae are firstly compared locally in the two fingerprints, then a global comparison score is derived by integrating the outcome of local minutiae comparisons.

The modern minutiae-based recognition systems are based on local descriptors, which encode the relationships between each minutia, namely reference minutia, and its neighboring minutiae in terms of rotation and translation invariant measures. These descriptors are mainly known as "local minutiae structures" in the literature [84], but they are sometimes called "local minutiae descriptors" or simply "minutiae descriptors" [37]. The local region covered by each descriptor is usually determined based on either considering the k nearest neighbor minutiae

[1] In biometrics literature, e.g., in [84], the use of "matching" is much more common than that of "comparison", however according to the recent harmonized biometric vocabulary developed in ISO/IEC 2382-37:2012 [53], the use of "matching" as a synonym for "comparison" is depreciated. Therefore, we tried to adapt to this harmonized vocabulary as much as possible throughout this thesis.

to the reference minutia, or considering a fixed-radius area around the reference minutia.

Minutia Cylinder-Code (MCC) is one the most recent local minutiae structures proposed by Cappelli et al. in 2010 [18] as a fixed-radius descriptor. It can also be considered as the state-of-the-art local structure based on its excellent performance for minutiae-based recognition reported by several independent research groups [21, 38, 94]. Other than the excellent accuracy as a fixed-length and rotation/translation invariant minutiae descriptor, it has several other advantages such as efficient bit-based representation for fast comparisons, parallel implementation for very fast and large-scale comparisons [20], and also a very good performance for fingerprint indexing [19] and template protection [40]. To the best of our knowledge, no other local minutiae structure proposed in the literature has shown such a high and balanced performance and that is why we have chosen the MCC as the baseline minutiae-based comparison method in this thesis. Minutiae-based comparison using local minutiae structures generally involve two main steps:

1. **Local comparison:** In this step, the local minutiae structures from two fingerprints are compared locally and a local similarity score is usually computed for every possible pair of descriptors from the two fingerprints to be compared.
2. **Consolidation:** In this step, the local similarity scores are combined into a single value called global comparison score, which denotes the overall similarity between the two fingerprints.

Biometric data quality can be estimated subjectively or objectively and expressed using global or local quality measures. Global quality measure of a biometric sample is a value showing the degree to which the sample is free of the degradation known to harm the recognition performance. Local quality measures represent the quality of local parts or regions within a biometric sample. Quality of biometric data can also be taken into account either locally or globally for building more accurate biometric recognition systems. Local quality measures are either combined into a global quality measure or directly embedded into the recognition techniques. For example, most of the local quality measures proposed for fingerprint images have been used for estimation of the global quality measures [6]. Minutiae quality have been used to improve the performance of minutiae-based comparison methods, e.g., in [13, 112], but mainly for global minutiae comparisons, where alignment is required.

The focus of this thesis is on direct incorporation of the local quality measures into the state-of-the-art minutiae-based comparison methods, particularly those based on the MCC, in order to improve their recognition performance.

1.1 Thesis objective

The ultimate goal of the research work presented in this thesis is in fact to build more accurate minutiae-based biometric recognition systems via embedding local quality measures. A motivating observation at the beginning of this work was the fact that there was no quality factor (especially local quality) considered in developing the state-of-the-art minutiae-based recognition methods, in particular those based on the modern local minutiae descriptors such as the MCC. This observation led us to the main objective of this thesis, which has been, developing new methods for embedding local quality measures, especially the minutiae quality, in the MCC-based comparison methods in order to improve their recognition performance.

1.2 Contributions

Main contributions of this thesis can be summarized as follows:

1. A new type of local quality measures is introduced to be associated with local minutiae descriptors; in particular, the cylinder quality measures have been introduced as generalization of minutiae quality to represent the quality of the MCC descriptors [61]. We have also proposed two general approaches for estimating such quality measures: either 1) using minutiae quality, or 2) using fingerprint quality maps for local quality assessment of the fingerprint image within the local area of each descriptor [58].

2. A novel and efficient quality-based consolidation method is proposed for embedding minutiae quality as well as cylinder quality measures in MCC-based comparison [61]. This method is not computationally expensive and does not involve any additional parameter or training step. However, the recognition performance is shown to be generally improved using this method compared to that achieved by the state-of-the-art MCC-based comparison methods. This is validated by extensive experiments on various fingerprint databases and in different recognition scenarios.

3. A supervised method is also proposed to modify the local similarity scores using local quality measures in order to obtain better recognition performance [60]. This method is based on a binary classification model, which needs labeled minutiae information for training. Therefore, we have used synthetic fingerprints generated by the Synthetic Fingerprint Generator (SFinGe) [14] to create a set of genuine/impostor descriptors needed for training such a classifier.

Other contributions of the thesis are as follows:

1. A new approach is proposed for taking the minutia or cylinder quality measures as basis to discard low-quality elements from local similarity matrix during local comparisons [59]. This approach is shown to be able to improve the recognition performance, especially where the number of extracted minutiae is relatively high in the fingerprints.
2. A comparative evaluation of cylinder quality measures using various local quality assessment methods is carried out for MCC-based comparisons.
3. The application of the proposed framework is investigated for the challenging problem of latent fingerprint and palmprint identification. This is done using special variants of the proposed quality-based consolidation method designed for embedding subjective [57] and objective [58] cylinder quality measures.

1.3 Outline of the thesis

The rest of this thesis is organized as follows:

In Chapter 2, we comprehensively review the literature and present the relevant state-of-the-art methods for minutiae-based biometric recognition as well as incorporation of quality measures in such biometric systems.

In Chapter 3, we introduce cylinder quality measures as a new type of local quality measures associated with the MCC descriptors. We also propose two general approaches for estimating cylinder quality measures and present a set of candidate local quality features to be included in such an estimation.

In Chapter 4, we propose two novel methods for embedding local quality measures, e.g., minutiae quality or cylinder quality, in MCC-based comparison methods. The first method is based on discarding low-quality elements from local similarity matrix during local comparisons. The second one is an efficient quality-based consolidation method, where the quality of MCC pairs is proposed to play a key role in selection of the final candidate pairs contributing to the global comparison score. The results of several different evaluations on various fingerprint databases from FVC2006 [16], FVC2004 [83], and FVC2002 [82] are also presented in this core chapter, showing the favorable performance of the proposed methods.

In Chapter 5, we present a supervised method for embedding any type of local quality feature including cylinder quality measures in minutiae-based comparison methods. This method is based on a binary classification model which is used to modify the local similarity scores using local quality measures. In order to train such a classifier, we use synthetic fingerprints generated by the SFinGe, as they contain labeled ground truth minutiae information. Finally, we discuss the potentials and weaknesses of synthetic fingerprints to be used for training in such an approach.

In Chapter 6, we evaluate cylinder quality measures based on different local quality assessment methods for MCC based fingerprint comparisons. The effect of some other parameters are also investigated in this chapter, such as weight of central region and quality block size in the cylinder quality measures.

In Chapter 7, we investigate our proposed framework for the challenging cases of latent fingerprint and palmprint identification. In fact, the variants of the proposed quality-based consolidation method are evaluated for embedding subjective or objective local quality measures in such cases.

In Chapter 8, we wrap up the main conclusions drawn in the scope of this thesis, and propose some lines of research as possible future directions.

2 State of the art

2.1 Biometric recognition systems

Biometrics refers to the task of recognizing people based on their biological or behavioral characteristics [65]. Biometric recognition have been widely used for many years in security and forensic applications. Access control, banking, travel documents, and Automated Border Control (ABC) are among famous examples for the security applications. The forensic applications include evaluation of evidence for criminal cases based on the biometric samples collected from crime scenes. Automating the biometric recognition is a difficult problem which has been under study for over 50 years [103] as an interesting pattern recognition application, yet it is considered challenging as the state-of-the-art biometric systems are still prone to errors [65].

Biometric recognition systems are mainly used for either one of two purposes:

1) **Verification:** aims at answering the question: "Is this person the individual who is claimed to be?". In other words, biometric verification is the task of verifying that a person is the individual that they claim to be, based on comparing their biometric sample with a previously collected sample from that person.

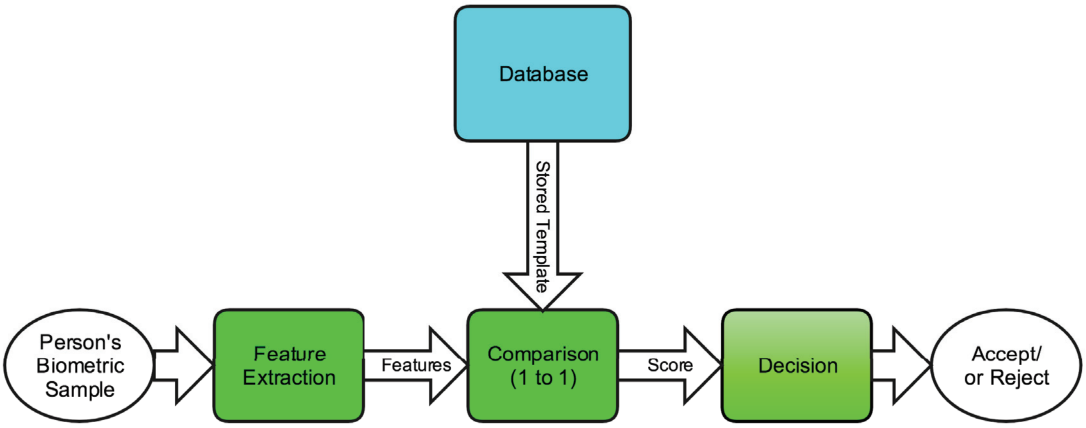
2) **Identification:** aims at answering the question: "Who is this person?". In other words, biometric identification is the task of identifying an individual based on comparing their biometric sample against a database of previously collected samples.

Nonetheless, biometric systems do not always operate fully automatically. For example in forensic domain, they are often used in a semi-automatic manner to sort a list of candidates and leave the final decision to a human expert [36].

The first interaction of persons with a biometric recognition system takes place during Enrollment phase, when their biometric samples are collected and stored in a database for later comparisons. In many cases, a specific representation of the acquired sample, called template, is stored in the database instead of original sample itself.

The main stages in any biometric recognition system include feature extraction, comparison and decision modules, as shown in Figures 2.1 and 2.2 representing verification and identification respectively. In the following sections, we discuss these stages in more details.

Figure 2.1 – Biometric Verification System



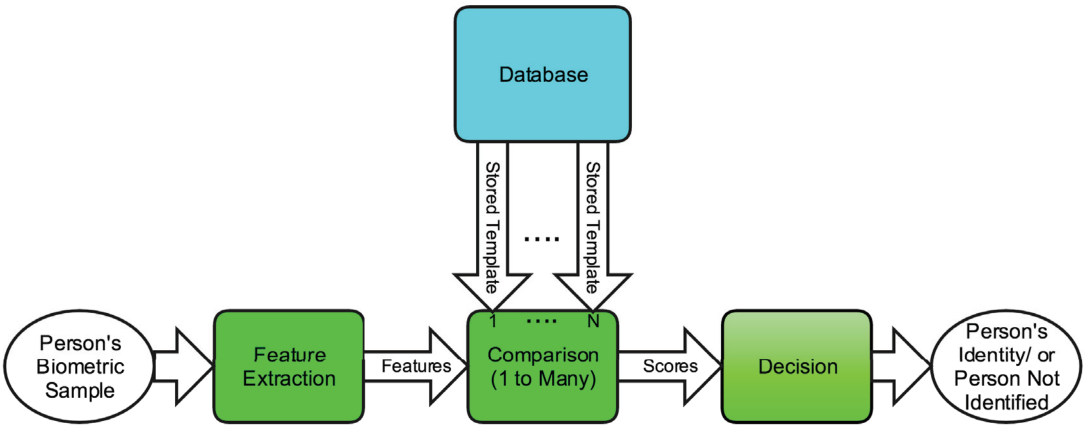


Figure 2.2 – Biometric Identification System

2.2 Feature extraction

Feature extraction is defined as the process of building pertinent representations (features) of the original data. Feature extraction can also be regarded as a dimensionality reduction process since it usually reduces the number of variables involved in the data. The feature-level representation of the data, i.e., the output of feature extraction process, is then used by the classifier for comparisons. Among typical examples are minutiae, which are known as the most critical features for fingerprints.

2.2.1 Global vs. local features

Cognitive neuroscientists and neuropsychologists have found that combination of global and local information is crucial for robust recognition of objects and traits [49], where different global and local features offer complementary information [110]. Biometric recognition systems like any other pattern recognition systems use global features describing the biometric sample as a whole, and/or local features representing local parts or points within the sample. Global features often represent the entire sample with a single vector. On the other hand, local features are computed at multiple locations within the sample, representing the local characteristics. However, they usually require special classification methods to handle cases in which there are a variable number of feature vectors. In more advanced techniques, some local descriptors are built to encode the relationship between the initially extracted local features within a predefined local area in terms of some measures invariant to global transformations such as rotation, translation and scaling.

2.3 Comparisons and decisions

As shown in Figures 2.1 and 2.2, the feature-level representation of a person's biometric sample then goes through a comparison step where it is compared with a previously stored representation, typically resulting in a comparison score. This score ideally shows how similar the two representations are.

In the case of verification, it is compared with a stored representation belonging to the claimed identity. Then, by setting a threshold on the resulting comparison score, a binary decision is made for either accepting or rejecting the claimed identity.

In the case of closed-set identification, it is compared with the set of all representations stored in the database, normally providing a set of comparison scores. Then, based on the ranking of these scores, the most similar representation in the database determines the person's identity. However in open-set identification, the corresponding score must also pass a fixed minimum threshold for identification to be valid. Otherwise, the person is said to be "not identified".

In forensic science, the comparison scores are often used for sorting a list of candidates, but not making any decision. In such cases, the decision is left to be made by human experts [36].

A variety of methods and classifier types exist for biometric comparisons. In some cases, the comparison task is divided into two parts: local and global comparisons. During the local comparisons, particular local regions within the biometric samples are compared first using some local features/descriptors. Then, a global comparison score is obtained by leveraging the results of the local comparisons.

2.4 Quality of biometric data

In general, there are many definitions for data quality. By searching for "data quality" in Wikipedia, one can find that "data is generally considered high quality if they are fit for their intended uses in operations and decision making.". Similarly biometric data can be considered to be of good quality if the data is fit for person recognition. However it is a very broad definition and there are several other connotations for biometric sample quality, such as:

- The degree to which the biometric sample is free of degradation known to (negatively) influence the recognition performance.
- The degree of usefulness/fitness of the biometric sample for their intended use (person recognition) [12].
- The degree of extractability of the features used for recognition [95].
- The amount of information or texture richness present in the biometric sample [95], e.g., ridge clarity in fingerprints.

In this thesis, the term quality is considered more along the first definition, where the quality of a biometric sample can be defined as the degree to which the sample is free of degradation. By degradations we mean those which are known to contribute to the recognition errors, affecting the recognition performance (in a negative sense).

The recognition errors in biometric systems come from different sources such as noise and artifacts in biometric samples, sensing conditions, sensor characteristics and so on. These sources of degradation are either purely related to the person or related to the interaction between the person and sensors. Many of these factors would ultimately matter in the ability of the biometric systems for correct recognition. Quality of biometric data can be taken into account when building a biometric system for better performance. That is why the quality assessment algorithms are increasingly deployed in operational biometric systems.

The ISO/IEO 29794-1 standard [55] specifies a framework to interpret the biometric sample quality. According to that standard, the quality of a biometric sample can reflect three different aspects:

1. **Character** of the sample: reflecting the inherent and natural discriminative properties of the sample's source. For example, an altered fingerprint has a poor character.
2. **Fidelity** of the sample: reflecting how similar the sample is to its source.
3. **Utility** of the sample: reflecting the predicted impact of the sample on the overall performance of a biometric recognition system. Utility depends on both character and fidelity of the sample.

The most important aspect among those mentioned above is the last one, i.e., the utility-based quality measures, which are going to be more predictive of the recognition performance.

In terms of measurement approach, quality measures are categorized into subjective and objective measures [5]. Subjective quality measures are estimated with human intervention, while the objective ones are derived automatically. Manual annotations about the size of fingerprint or amount of dirt can be considered as examples of subjective quality measures for the fingerprint [95].

Algorithms for objective quality assessment of fingerprint images are probably the most advanced, due to the fact that the fingerprint capturing is relatively controlled, which minimizes the number of possible extraneous conditions that could deteriorate the scan.

In this thesis, we are mostly interested in objective quality measures, but we also consider subjective quality measures for the case of latent fingerprint identification.

There are other quality related factors like age, known as metadata quality [47], which have been considered for embedding into biometric recognition systems together with other quality measures (e.g., in face and speaker verification [35, 69]).

2.4.1 Global vs. local quality measures

Quality measures are numerical values representing the quality of biometric data. Global quality measure is a single value representing the quality of a biometric sample entirely, while local quality measure represents the quality of a local region within the biometric sample [12]. Local quality in a biometric sample is important to be addressed especially when there are significant variations in quality from region to region. In such a case, global quality assessment without considering the local quality variations might result in a poor quality estimation. Local quality measures can also be very helpful in local comparison methods using local features.

2.4.2 Embedding quality measures into biometric systems

As explained in Section 2.4, the quality of biometric data can significantly affect the ability of biometric systems for correct recognition. Therefore, quality measures can be taken into account when building a biometric system to improve its recognition performance. In general, global quality measures have been embedded in the biometric systems via different approaches, such as:

1. For discarding low-quality samples or suspending the decision until a sample with sufficient quality is available [95, 43].

2. As a parameter controlling how to process each sample differently [95], for example by quality-based weighting.

3. Assisting in combination of multiple biometric modalities or classifiers, known as quality-based fusion [95].

Quality measures can be employed in feature level, score level or decision level, but most of the proposed methods operate in the score level. These methods usually consider quality measures either as auxiliary features, e.g., in Q-stack [72, 71], or as control parameters, e.g., in Maurer and Baker's Bayesian belief network [85]. Poh et al. in [95] proposed general models to unify different quality-based fusion methods within a Bayesian framework, where the fusion approaches are generally categorized into feature-based and cluster-based categories. Considering a general case, where several modalities exist for fusion as well as several quality measures for each modality, they modeled each fusion approach (feature-based or cluster-based) with a unique Bayesian network in the presence of either generative or discriminative classifiers. Then a decision rule is derived by inference for each network. The key point which needs to be addressed carefully for such a fusion is the dependency between three sets of variables: quality measures, features, and classes.

On the other hand, the local quality measures have been mostly used to be combined into a global quality measure, but they can also be used to:

1. discard the low-quality parts from a biometric sample before comparison, or
2. weight or process the local parts differently for their contribution to the global comparison.

Most of the research work done for embedding quality measures into biometric recognition systems have been focused on global quality measures and much less done on the local level, mainly due to the fact that it is more difficult to evaluate the level of degradation in local regions and also their contribution in global comparison performance.

2.5 Minutiae-based biometric recognition

2.5.1 Fingerprint comparison

Sir William Herschel used fingerprints for the first time to identify criminals in India around 1860, but it was Sir Francis Galton who actually provided a scientific basis to statistically measure the individuality of fingerprints for each person [41].

Fingerprint is the most widely used biometric modality for both security and forensic applications [26]. Although fingerprint recognition is not the most accurate among different biometric modalities, it is considered as one of the best when it comes to the balance between accuracy, robustness, speed, and required resources.

Fingerprint comparison is a crucial step in both fingerprint verification and identification. The fingerprint feature extraction provides up to three levels of features, which can then be used for comparison [84]: Level 1 features are mainly global level information about ridge line flow and singular points like core and delta in a fingerprint. Level 2 features are local level information, mainly referring to minutiae details. Minutiae represent the bifurcation and termination of the fingerprint ridges, which are observable in images with a relatively high resolution (typically 500 pixels per inch (ppi)). Level 3 features are very fine details inside the ridges like sweat pores, which can only be observed in very high resolution images (~ 1000 ppi).

A vast majority of the efforts for fingerprint comparison has been focused on minutiae-based comparison, as they are believed to be the most discriminating features of the fingerprint. [84].

Minutiae-based comparison methods are divided into global and local comparison methods. Global minutiae comparison is normally based on finding correspondences between two sets of minutiae after some global alignments. The local minutiae comparison techniques have been proposed in order to address some weaknesses of global minutiae comparison [84] such as non-robustness to nonlinear distortions, need for accurate alignments, and being computationally demanding. The modern minutiae-based techniques are based on local minutiae structures which are in fact the descriptors encoding the relationships between each minutia and its neighboring minutiae in terms of some invariant measures with respect to rotation and translation.

Local minutiae structures (aka local minutiae descriptors) are generally built under either one of two assumptions:

1. **Nearest Neighbor:** these descriptors are created by considering a fixed number of minutiae around a central minutia. The most notable comparison methods based on this type of local structures are Bozorth3 method developed at NIST [109], and the method developed by Jiang and Yau in [67]. It is known that handling missing or false minutiae is usually more problematic using this type of structure than fixed radius.

2. **Fixed Radius:** these descriptors are created by considering all the minutiae existing within a fixed distance from a central minutia. The most notable comparison methods based on this type of local structures are developed by Ratha et al. [96], developed by Feng [37], and MCC developed by Cappelli et al. [18]. This type of structures might be prone to errors with respect to the minutiae near the border of each descriptor.

According to a 2015 comprehensive survey [94], there are over 80 minutiae-based local matching methods already published for fingerprint comparison. However, after an extensive performance evaluation on several databases, the authors have concluded that the following four methods are the most accurate for fingerprint verification: MCC [18], Bozorth3 [109], Jiang's [67], and Deng's [33]. Based on various statistical tests performed in [94], the recognition performance of these four methods is shown to be significantly higher than the other methods.

In terms of the computation time, the fastest algorithm among them is Jiang's, followed by Bozorth3, MCC, and Deng's.

2.5.2 Palmprint comparison

Palmprint comparison has been already employed in various biometric recognition systems for purposes such as access control [70]. On the other hand, palmprints are of special interest in forensic applications, due to the fact that a considerable portion (~ 30%) of latent prints retrieved from crime scenes are actually from palms [74, 34].

In comparison with fingerprint, palmprint includes a larger area (palm vs. finger), which is known for having a special set of features, called flexion creases. The creases are in fact the discontinuities in the palmar ridge patterns, divided into major creases (aka principal lines) and minor creases (aka wrinkles). The pattern of palm creases is considered a reliable trait for biometric recognition of each individual [8].

The palmprint comparison methods developed so far can be divided into two main categories, based on the resolution of underlying images:

1. **Low-resolution palmprint comparison:** When the palmprint images have a relatively low resolution of around 100 ppi, in which only the major creases can be detected and no minutia is observed [70]. The palmprint recognition systems developed for access control applications mostly fall into this category, and usually involve the comparison of full palmprints. The basic methods, e.g., [48], [66], compare the major creases extracted using different edge detection approaches. Some other methods extract features for instance using Gabor filters [116] or Discrete Cosine Transform (DCT) [68], and compare them later on, sometimes after projecting them into a subspace, e.g., via Principal Component Analysis (PCA) [80] or Linear Discriminant Analysis (LDA) [111, 68]. In a group of methods, the original palmprint images are first transformed into a separate domain for example by Fourier [76] or wavelet [117] transform. Then the comparison procedure is performed in that domain, either locally [73], or globally [117].

2. **High-resolution palmprint comparison:** When the resolution of palmprint image is high enough, for example more than 400 ppi, the ridges can be observed, making it possible to extract a more discriminative set of features, in particular the minutiae, from the image. Minutiae-based palmprint comparison is mainly suitable for forensic applications, since 1) the standard resolution of images is rather high (about 500 ppi) in such cases, and 2) unlike the usual full-to-full comparisons in access control, latent-to-full comparisons must be supported in most forensic cases, where minutiae can play the major role [88]. The minutiae-based comparison is rather challenging for palmprints, because there are usually a large number of minutiae, lots of missing and false minutiae, and large nonlinear distortions existing in each palmprint image. However during the past few years, major efforts have been done to develop accurate methods for high-

resolution palmprint comparison, most notably in [75], [62], [32], [79], and [17]. All of them began with the same procedure as fingerprint minutiae extraction in general but add some modifications in detail consistent with the palmprint special characteristics. Jain and Feng in [62] employed a region-growing method to estimate the local ridge orientation and frequency in a palmprint, which is then used to extract minutiae. They have also proposed to use a local minutiae descriptor, called MinutiaCode, together with an alignment-based method for minutiae matching. The global similarity score between two palmprints is finally obtained via a weighted average of two scores coming from different matching methods, one based on the MinutiaCodes and the other based on the orientation field alignment. Dai et al. in [32] proposed to use multiple features including minutiae, density map, orientation map, and major creases together in order to improve the accuracy of palmprint comparisons. Later a faster and more accurate version of this method is proposed in [31] based on segmenting the palmprint images into multiple small regions, followed by a Bayesian fusion of the regional comparison scores. Spectral Minutiae (SM) representation originally introduced for fingerprint verification [113] has also been used for high-resolution palmprint comparison, where the performance is shown to be worse compared to fingerprint comparison [107]. However the authors have later proposed a modification to this approach in [106], where it is shown that dividing the full palmprint into three smaller regions (namely thenar, hypothenar and interdigital) followed by a fusion of regional SM-based comparison scores can significantly improve the performance compared to the original version [105]. In [17], Cappelli et al. have also proposed an updated minutiae extraction procedure together with a slightly modified MCC-based approach for high-resolution palmprint comparison. Most recently, Liu et al. [79] proposed a minutiae-based palmprint comparison based on first clustering the minutiae into several groups sharing similar local characteristics. Then a coarse matching is performed within each cluster and the global score is obtained finally through a minutiae match propagation algorithm. To the best of our knowledge, among all the methods mentioned above, the MCC-based approach proposed in [17] achieved the highest accuracy for partial-to-full and full-to-full palmprint comparison based on the experiments performed on the publicly available high-resolution palmprint databases, e.g., it achieves the Equal Error Rate (EER) of less than 0.01 percent on THUPALMLAB database [4]. It is also shown to be among the fastest comparison algorithms next to Liu's [79].

Consistent with the objective of this thesis, we focus mainly on the second category, i.e., minutiae-based methods for high resolution palmprint comparison.

2.5.3 Latent print comparison

Latent print is typically an incomplete impression of a finger or a palm, which is usually recovered from an object surface in a crime scene. A latent print is either a latent fingerprint if it is from a finger, or a latent palmprint if it is from a palm. Roughly more than 30% of latent prints retrieved from the crime scenes are latent palmprints. Latent fingerprints have been used as evidence in forensic applications for more than a century [9].

Latent print comparison is much more difficult than plain or rolled fingerprint comparisons, due to existence of rather small latent-to-full overlapping area and large amount of noise and distortion in the latent prints. Therefore, human intervention is often required during the latent print comparison process, for example for orientation estimation, minutiae extraction and quality assessments. Before feature extraction, a latent print normally goes through a pre-processing step, during which ridge quality is enhanced and the area containing ridge patterns is segmented. Although there are rather accurate methods for automatic minutiae extraction from plain or rolled fingerprints, extracting minutiae from latent fingerprints in a fully automatic way is not yet that reliable. Hence, the minutiae in latent fingerprints are usually marked by trained examiners, which can eventually introduce an interoperability problem between this kind of minutiae and those extracted automatically [93]. An Integrated Automated Fingerprint Identification System (AFIS) is then used to compare the manually marked features with the set of background fingerprints in a database. The AFIS lists for example the top 50 probable matches to be manually verified by the examiners. Such a system is said to be operating in “Semi Lights-Out” mode [36], where some human intervention is permitted. However, the community is moving more and more towards the systems operating in "Lights-Out" mode [86], where no human intervention is required throughout the process. In other words, there has been a series of works recently to develop an automated system for different steps of this process, such as segmentation, quality assessment and enhancement, feature extraction and comparison [97]. During the past few years, the National Institute of Standards and Technology (NIST) has also been very active at evaluating the accuracy of commercial systems for automated latent fingerprint identification using features marked by experienced examiners [51, 50].

We review the latent quality assessment in Section 2.6.3, but regarding the other steps, Jain and Feng [63] proposed to use a semi-automated latent fingeprint matching method by considering several manually annotated features such as orientation map, ridge flow, minutiae, and quality map. In [92], Paulino et al. used a descriptor based Hough transform for minutia alignment in latent fingerprint. MCC has been used there as the local descriptor. Arora et al. [7] proposed to use feedback from a rolled/plain fingerprint for updating the extracted features of the latent fingerprints in order to improve the matching performance. In fact, all the methods proposed for semi-automated latent fingerprint matching during the last years, are not solely based on minutiae, but use other subjective and objective features and information together with manually marked minutiae to improve latent matching accuracy [97].

2.6 Local quality measures in hand biometrics

2.6.1 Local quality measures of fingerprint

Local quality measures normally rely on the local features of biometric samples. In the case of fingerprint images, each image is firstly divided into several blocks and then a local measure of quality is computed for each block within the image. This block representation of the local quality measures is usually referred to as fingerprint quality map. Fingerprint quality maps are mainly used to obtain a global quality measure for the entire fingerprint image. The local quality in each block of the fingerprint quality map is generally estimated based on either one or a combination of these main types of local features [12]:

1. **Orientation:** Local direction of the ridges in the image.
2. **Gabor features:** Gabor filter responses at a given location in the image.
3. **Power spectrum:** Power spectrum of an image region.
4. **Intensity statistics:** Statistics on the intensities of pixels in the image.

1. Orientation based local quality measures

This type of quality measures use the fingerprint orientation map, containing the information about local ridge directions, in order to compute some local quality measures in each block.

Lim et al. [77] proposed several local features for estimation of local quality measures based on fingerprint orientation information. The most notable measure proposed by them are Orientation Certainty Level (OCL).

The OCL measures the energy concentration along the dominant ridge flow orientation in each block.

Later, Chen et al. [28] proposed another major local quality measure based on orientation features, called Orientation Flow (OF) which measures the ridge flow continuity based on the absolute orientation difference between a block and its neighboring blocks.

2. Gabor filter based local quality measures

Gabor filters with different orientations and frequencies are filter banks representing the local texture information of an image. They are widely used in image processing and analysis, e.g., in fingerprint image enhancement.

Shen et al. [98] proposed a method to measure the local quality of fingerprints using Gabor filters. Gabor filter responses with m different directions are computed at a given block. The standard deviation of the m responses is used then to determine the quality of each block. For high quality blocks, there will be a high response in one or a few directions (strong ridge direction). But in low quality blocks there is no dominant response in any direction, resulting in a lower standard deviation.

Olsen et al. [90] modified this method in a way that it can operate on a pixel basis as well. The size of the filter bank is also used to determine a number of directional filters evenly across the half circle.

3. Local quality measures based on power spectrum

Power spectrum is often computed using Discrete Fourier Transform (DFT) for different image regions to measure local information present at those regions, such as local quality.

Lim et al. [78] proposed a spectral analysis algorithm to compute the local quality measures for fingerprints. Firstly the ridge valley structure is modeled using a 2-dimensional sinusoidal wave in each block, then the DFT is used to determine the frequency of the sinusoidal wave. Poor quality blocks will not show a dominant frequency within the usual range of ridge frequencies.

4. Local quality measures based on pixel intensity statistics

A common way for estimating local quality measures is the statistical evaluation of pixel intensities in the image.

Local Clarity Score (LCS) proposed by Chen et al. [28] is one of the most commonly used local quality measure of this kind. It measures the clarity of ridge and valleys in each block by applying linear regression to determine a gray-level threshold, based on which the pixels are classified as ridge or valley. By comparing with the normalized ridge and valley width, a ratio of mis-classified pixels is finally determined as the local clarity score.

Ridge valley Uniformity (RVU) proposed by Lim et al. in [77], is another local quality measure in this category, which is based on evaluating the width of ridges and valleys. The RVU measures the consistency of the ridge and valley widths based on the ratio of ridge to valley width. It is useful for detecting the ridges that are unreasonably thick or thin.

Local quality measures based on combination of the features Other than the four major groups presented above, there are other methods which consider a combination of these features to estimate the local quality within a fingerprint region. A well-known example is the NIST Biometric Image Software (NBIS) [42], whose MINDTCT package provides a fingerprint quality map via combination of different local features. The NBIS MINDTCT quality map is then used for estimating quality of each minutia and also for obtaining the NIST Fingerprint Image Quality (NFIQ) [102]. The NFIQ is computed via a 3-layer neural network classifier which takes as input 11 different quality features of fingerprint, mostly extracted from the MINDTCT quality map, and provides an integer measure of global quality for the fingerprint in 5 discrete levels, where 5 represents lowest quality and 1 represents highest quality. The NFIQ neural network is trained using 5244 fingerprint impressions manually divided into 5 different levels of quality [101]. In the recent development of the NFIQ, known as NFIQ 2.0 project [100, 10, 1], additional quality features such as those based on Gabor filters are going to be considered for estimation of the fingerprint global quality measure.

2.6.2 Local quality measures of latent fingerprint

Latent print is typically an incomplete impression (of a finger or palm) acquired under imperfect conditions, causing large distortions and background noise. That is why the ridge structure is often corrupted in latent prints and their quality is considered to be relatively low, compared to a normal fingerprint or palmprint obtained under controlled conditions. This makes the human intervention often necessary for examinations during the latent print identification process. The most common methodology for latent print examination is Analysis, Comparison, Evaluation, and Verification (ACE-V) [8, 30]. In each stage of the ACE-V process, the examiner needs to assess and take into account the varying levels of latent quality.

Latent quality assessment is one of the challenging tasks, which is usually done for a latent print by the examiner in order to assess its value as a forensic evidence [46, 25]. However, the human factors vary from person to person, which affects the consistency hence the reliability of the value assessments by different examiners. To overcome this deficiency, Yoon et al. in [115] proposed a method for objective quality assessment of a latent fingerprint based on averaging a quantitative measure of local ridge clarity and also taking into account the total number of minutiae marked in the latent print. Later in [114], they updated this quality measure, so called Latent Fingerprint Image Quality (LFIQ), by considering additional components such as a minutia reliability learned using a background dictionary of high-quality minutia patches. In [45], Hicklin et al. described a process which can be used by examiners or automated systems for evaluating the clarity of friction ridges in a latent print. To the best of our knowledge, there is no other attempt in the literature specifically developed for quality assessment of latent fingerprints. Both [115] and [114] aim at introducing an objective global quality measure for a latent fingerprint based on its local features. As in the case of LFIQ, local quality plays a major role in latent quality assessment, specially the minutiae quality since minutiae are considered as the most important features in latent examinations. In addition to the latent global quality, the quality of the manually extracted minutiae is usually assessed by the examiners.

2.6.3 Local quality measures of palmprint

High-resolution palmprints are similar to fingerprints in many aspects when it comes to local level. Therefore, most of the algorithms proposed for local quality assessment of fingerprints can also be adjusted for estimating the local quality in high-resolution palmprints.

2.7 Minutia Cylinder-Code (MCC)

Minutia Cylinder-Code (MCC) is one of the most recent local minutiae structures proposed by Cappelli et al. [18], which can be fairly considered as the state-of-the-art[1] of its kind [38, 94].

Starting from a minutiae template, the MCC is computed as a fixed-length minutiae descriptor to be invariant to rotation and translation, robust to skin distortions, computationally fast and simple, and having the potential of easy bit-based implementation as well. Inspired by the fixed-radius point descriptors much used in shape description [11], the distance of one minutia to all its neighboring minutiae is considered as basis for creating this descriptor. In addition to distance, the angular difference between direction of the minutiae is taken into account using an additional dimension, finally creating a discretized 3D cylinder-shaped structure for each minutia, whose base and height are related to the spatial and directional information, respectively. Figure 2.3 shows an MCC descriptor with five minutiae in its neighborhood.

The MCC is based on a local structure created for each minutia, simply called cylinder. A minutia is usually determined with a triplet $m = \{x_m, y_m, \theta_m\}$, where (x_m, y_m) is the minutia location within the fingerprint image expressed in pixels, and θ_m is the minutia direction in the range of $[0, 2\pi[$. As shown in Figure 2.3, the cylinder associated to such a minutia is determined by a cylindrical local structure, whose base is centered at the location of the minutia. The cylinder radius and height are R pixels and 2π radians, respectively. The cylinder's base is aligned according to the central minutia direction θ_m and discretized into cuboid cells with the base size of $\triangle_S \times \triangle_S$ pixels and the height size of $\triangle_D$ radians. R, $\triangle_S$ and $\triangle_D$ are among the main parameters for cylinder creation. For example, for the common case of MCC16b descriptor [18], these parameters are proposed to be R= 70 pixels, $\triangle_S = \frac{2R}{16} = 8.75$ pixels, and $\triangle_D = \frac{\pi}{3}$ radians. Then a numerical value for each cell is calculated, which is supposed to estimate the likelihood of finding minutiae near the cell with a directional difference close to the angle associated to that cell. The directional difference of each minutia in this case is computed with respect to the central minutia direction, i.e., θ_m. The cell value is computed by sum of the contributions from all the minutiae existing in a close neighborhood of that cell. The contribution of each minutia to the cell is the product of two main factors; spatial and directional contributions.

- The **spatial contribution** of each minutia is determined by the normalized distance between that minutia and the center of the cell.

- The **directional contribution** of each minutia is computed based on how close is the cell angle to the directional difference between that minutia and the central minutia.

[1]Although the MCC is considered to have one of the highest performances among the public methods published in the literature, there are some commercial systems with even higher performances reported [81, 50].

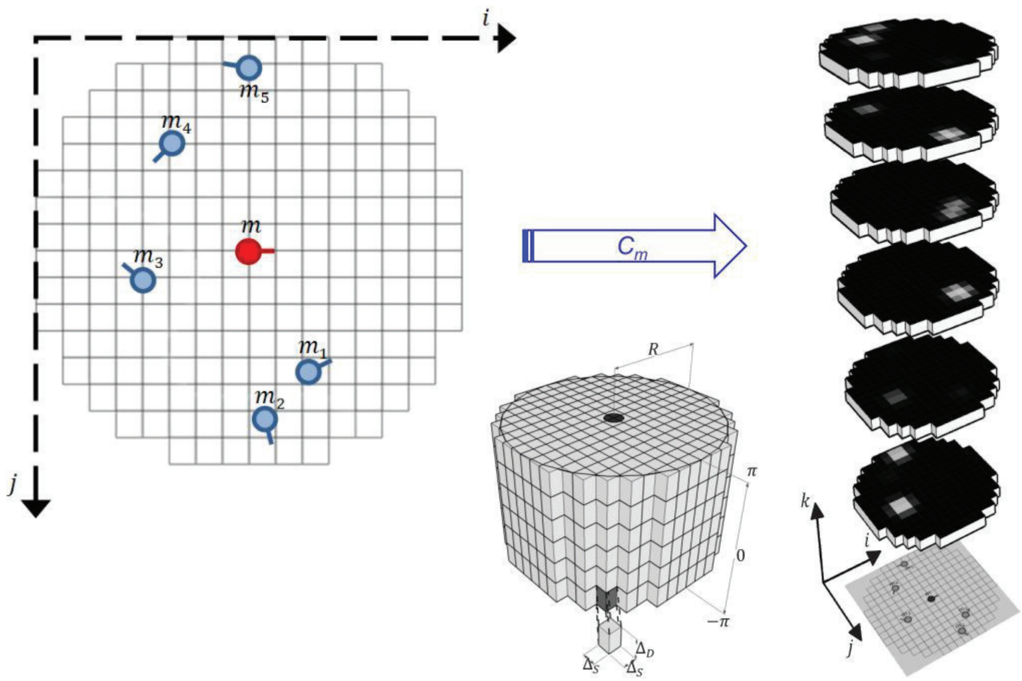


Figure 2.3 – MCC cylinder corresponding to one minutia. [18, 21]

2.8 MCC based comparison

Many modern minutiae based fingerprint comparison methods employ a local matching algorithm, usually followed by a consolidation stage, and finally a procedure to obtain a global comparison score between the two fingerprints. MCC based fingerprint comparison involves the same stages in general. In the local matching stage, a local similarity score is computed for every possible pair of MCC descriptors from the two fingerprints. Then, the local similarity scores are combined into a single value called global score, which denotes the overall similarity between the two fingerprints, being used for their comparison.

More precisely, given two MCC templates, say $A = \{a_1, a_2, ..., a_{n_A}\}$ and $B = \{b_1, b_2, ..., b_{n_B}\}$, we assume that $\Gamma(a_r, b_c)$ is the local similarity score between two cylinders a_r and b_c from the templates A and B respectively. r and c denote the cylinder indices in the templates A and B respectively ($1 \le r \le n_A$, $1 \le c \le n_B$). Hence there are $n_A \times n_B$ MCC pairs in total. Local similarity scores can be also represented in the form of a matrix Γ with n_A rows and n_B columns. In the pre-selection step, a set of candidate pairs is pre-selected among all $n_A \times n_B$ pairs available in Γ. In the relaxation step, the compatibility with other pairs is also taken into account using second-order compatibility measures, in order to relax the local similarity scores of the candidate pairs using an iterative procedure. Finally a small number of pairs (usually between 3 to 12) will be selected for computing the global score between the two templates. These main steps are shown in Figure 2.4.

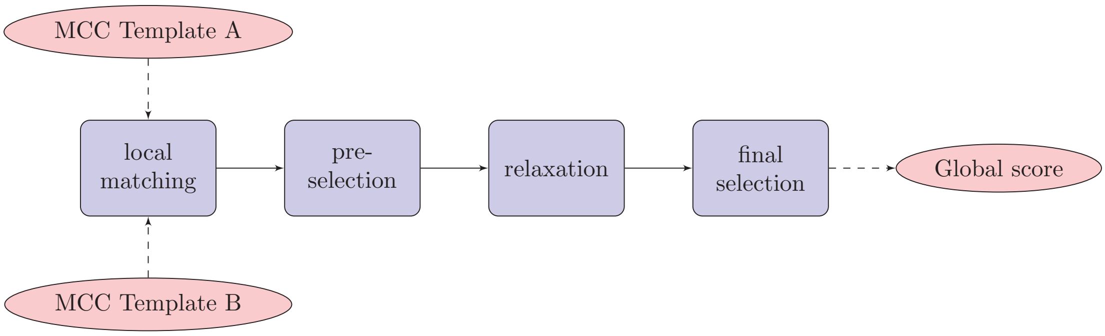


Figure 2.4 – Main steps in MCC based fingerprint comparison

2.8.1 Local similarity scores

Given two fixed-length vectors c_a and c_b of floating-point values in the range $[0,1]$ corresponding to the cylinders C_a and C_b, respectively, the local similarity score $\Gamma(c_a, c_b)$ is computed as follows:

$$\Gamma(c_a, c_b) = \begin{cases} 1 - \frac{\|c_a - c_b\|}{\|c_a\| + \|c_b\|} & \text{if } d_\theta(a,b) \le \delta_\theta \\ 0 & \text{otherwise} \end{cases},$$

where $\|.\|$ denotes the Euclidean norm and $d_\theta(a,b)$ is the angular difference between the central minutiae of the two cylinders, and δ_θ is a parameter related to the maximum rotation allowed between two fingerprints. A more common case is when the vectors are binarized by setting a threshold (usually 0.5) on the floating-point values. If the corresponding binary vectors are assumed to be c'_a and c'_b in this case, the local similarity score can be computed much faster using a bitwise XOR operator as follows:

$$\Gamma(c'_a, c'_b) = \begin{cases} 1 - \frac{\|c'_a \oplus c'_b\|}{\|c'_a\| + \|c'_b\|} & \text{if } d_\theta(a,b) \le \delta_\theta \\ 0 & \text{otherwise} \end{cases},$$

where $\oplus$ is the bitwise XOR operator.

2.8.2 Pre-selection of MCC pairs

Pre-selection of MCC pairs is usually the first step after computing local similarity scores, where a set of MCC pairs are selected from the pool of all possible pairs for next steps. There are several algorithms already proposed for this important step, including Local Similarity Sorting (LSS) and Local Greedy Similarity (LGS).

Algorithm 1 Pre-selection using Local Greedy Similarity (LGS)

0: $P = \phi$
1: **While** $|P| < n_R$
2: $(\hat{r}, \hat{c}) = \underset{(r,c)}{\arg\max} \left\{ \Gamma_{(r,c)} \mid \nexists (r', c') \in P \quad \text{with} \quad r' = r \vee c' = c \right\}$
3: $P = P \cup \{(\hat{r}, \hat{c})\}$
4: **End While**

Local Similarity Sorting (LSS)

According to Local Similarity Sorting (LSS) algorithm, n_R MCC pairs $\left(a_{r_k}, b_{c_k}\right)$, $k = 1, \ldots, n_R$, having the highest local similarity scores are pre-selected as candidate pairs. Since there might be some pairs in the candidate list with a common minutia, a modified version of LSS, called Local Greedy Similarity (LGS) have been proposed to discard such pairs.

Local Greedy Similarity (LGS)

According to the LGS, described in Algorithm 1, the n_R pairs are selected based on a greedy approach starting from the pairs with highest local similarity scores, but discarding those that contain at least a minutia already selected.

2.8.3 Relaxation

Through the relaxation step, the local similarity score of each pair is iteratively being modified based on its relationship with the other pairs. Let $\lambda_j^{(0)}$ be the initial similarity of pair j, i.e., $\lambda_j^{(0)} = \Gamma\left(a_{r_j}, b_{c_j}\right)$, then the relaxed similarity score at iteration i of the relaxation procedure is calculated as follows:

$$\lambda_j^{(i)} = \omega_R \cdot \lambda_j^{(i-1)} + \left(\frac{1-\omega_R}{n_R - 1}\right) \cdot \left(\sum_{\substack{k=1 \\ k \neq j}}^{n_R} \rho(j,k) \cdot \lambda_k^{(i-1)}\right), \tag{2.1}$$

where ω_R is a weighting parameter and $\rho(j,k)$ is the measure of compatibility between two pairs [18] $\left(a_{r_j}, b_{r_k}\right)$ and $\left(a_{c_j}, b_{c_k}\right)$. The compatibility measure $\rho(j,k)$ can be computed via Eq. 2.3, as explained below.

After executing n_{iter} iterations on all n_R pairs existing in P, the efficiency of pair j is calculated as follows:

$$e_j = \frac{\lambda_j^{(n_{iter})}}{\lambda_j^{(0)}}. \tag{2.2}$$

Compatibility measure

Given two minutiae $\left(a_{r_t}, a_{r_k}\right)$ from template A and two minutiae $\left(b_{c_t}, b_{c_k}\right)$ from template B, the compatibility measure $\rho(t,k)$ between two pairs $t = \left(a_{r_t}, b_{c_t}\right)$ and $k = \left(a_{r_k}, b_{c_k}\right)$ is calculated by Eq. 2.3 as the product of the normalized values of three rotation and translation invariant features, d_1, d_2, and d_3. d_1 denotes the similarity between the minutiae spatial distances. d_2 compares the directional differences in the two pairs, and d_3 compares the radial angles, according to the following equations:

$$\rho(t,k) = \prod_{i=1}^{3} \frac{1}{1+\exp\left(\tau_i^{\rho}\left(\mu_i^{\rho} - d_i\right)\right)}, \tag{2.3}$$

and

$$d_1 = \frac{\left|d_S\left(a_{r_t}, a_{r_k}\right) - d_S\left(b_{c_t}, b_{c_k}\right)\right|}{d_S\left(a_{r_t}, a_{r_k}\right) + d_S\left(b_{c_t}, b_{c_k}\right)}, \tag{2.4}$$

$$d_2 = \left|d_\phi\left(d_\theta\left(a_{r_t}, a_{r_k}\right), d_\theta\left(b_{c_t}, b_{c_k}\right)\right)\right|,$$

$$d_3 = \left|d_\phi\left(d_R\left(a_{r_t}, a_{r_k}\right), d_R\left(b_{c_t}, b_{c_k}\right)\right)\right|,$$

where μ_i^{ρ} and τ_i^{ρ} are the parameters of the normalizing sigmoid functions. d_S, d_θ, and d_R are the operators computing distance, directional difference, and difference between radial angles respectively, as follow:

$$d_R\left(a_1, a_2\right) = d_\phi\left(\theta_{a_1}, \operatorname{atan2}\left(-y_{a_2} + y_{a_1}, x_{a_2} - x_{a_1}\right)\right),$$

$$d_\theta\left(a_1, a_2\right) = d_\phi\left(\theta_{a_1}, \theta_{a_2}\right) = \begin{cases} \theta_{a_1} - \theta_{a_2} & \text{if } -\pi \le \theta_{a_1} - \theta_{a_2} < \pi \\ 2\pi + \theta_{a_1} - \theta_{a_2} & \text{if } \theta_{a_1} - \theta_{a_2} < -\pi \\ -2\pi + \theta_{a_1} - \theta_{a_2} & \text{if } \theta_{a_1} - \theta_{a_2} \ge \pi. \end{cases}$$

2.8.4 Final selection and global score

The number of final pre-selected pairs, n_P, is chosen in the range of $\left[min_{n_P}, max_{n_P}\right]$ using the following formula, depending on the minimum number of minutiae in two templates:

$$n_P = min_{n_P} + \left\lfloor Z\left(min\left(n_A, n_B\right)\right) \cdot \left(max_{n_P} - min_{n_P}\right)\right\rceil, \tag{2.5}$$

where $\lfloor . \rceil$ denotes the rounding operator and $Z(v)$ is the sigmoid function with parameters μ_P, σ_P as given in Eq. (2.6):

$$Z(v) = \frac{1}{1+e^{-\sigma_P\left(v-\mu_P\right)}}. \tag{2.6}$$

Figure 2.5 shows the value of chosen n_P with respect to the minimum number of minutiae in the two templates based on the parameters of the MCC SDK version 1.4. The n_P pairs with the

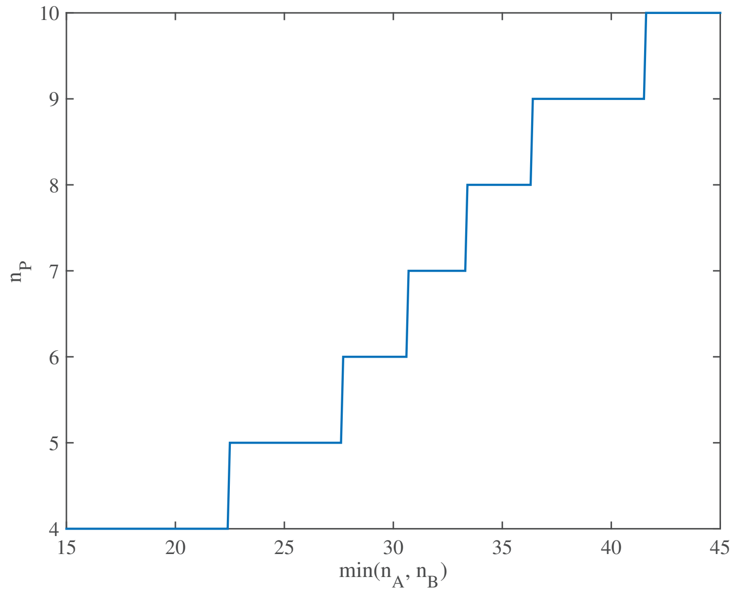


Figure 2.5 – The number of final MCC pairs (n_P) versus the minimum number of minutiae in the two templates.

highest efficiency e_j (Eq. 2.2) are finally selected, and the global comparison score ($Score$) is computed by averaging their relaxed similarity scores as follows:

$$Score = \frac{\sum_{j=1}^{n_P} \lambda_j^{(n_{iter})}}{n_P}. \tag{2.7}$$

It is worth noting that if there is no relaxation used for MCC based comparison, the pre-selection would be the final selection as well, i.e., $n_R = n_p$, and the local similarity scores will be used for final averaging rather than relaxed similarity scores.

2.8.5 MCC based palmprint comparison

MCC descriptors can be created for a set of minutiae extracted from a palmprint image following the same procedure as for fingerprints [17], but using a different set of parameters regarding the specific characteristics of a typical high-resolution palmprint image. Among these characteristics are the existence of much larger area, much more minutiae, and very large distortions. Most importantly, the cylinder radius is chosen about 30% larger with respect to the case of fingerprints (90 pixels instead of nearly 70 pixels). The maximum rotation between two palmprints are allowed to be π radians instead of , again much higher than that of fingerprints. Minimum and maximum number of final minutiae pairs are set almost 10 times more for palmprints. There is also an additional parameter limiting the number of pre-selected minutiae pairs to be maximum 300 for the relaxation. The number of iterations in relaxation phase is also chosen much higher for . The sigmoid parameters for computing both the compatibility measure and the number of final pairs have been updated accordingly. A normalization step is also added before pre-selction in order to penalize those minutiae which usually have high local similarity score with many others.

$$\hat{\Gamma}(r,c) = \left(1 - \frac{\sum_{\substack{i=1\\i\neq r}}^{n_A} \Gamma(i,c) + \sum_{\substack{j=1\\j\neq c}}^{n_B} \Gamma(r,j)}{n_A + n_B - 2}\right) . \Gamma(r,c) . \tag{2.8}$$

The term d_1 in compatibility measure (Eq. 2.3) is also updated according to Eq. 2.9 in order to allow larger discrepancies for larger distances. This makes the relaxation more tolerant to distortion:

$$d_1 = \frac{\left| d_S\left(a_{r_t}, a_{r_k}\right) - d_S\left(b_{c_t}, b_{c_k}\right)\right|}{max\left(d_S\left(a_{r_t}, a_{r_k}\right), d_S\left(b_{c_t}, b_{c_k}\right)\right)} . \tag{2.9}$$

2.9 Local quality measures in minutiae-based comparison

Incorporating local quality measures in minutiae-based matching has been an interesting problem considered in this context. Chen et al. for instance proposed a global minutiae matching by weighting minutiae correspondences based on their quality [29]. In [27], several methods have been investigated for embedding minutia quality scores in matching. Cao et al. also introduced a new term related to local quality, called minutia discriminability, and used it to improve the performance of global minutiae matching [13]. However, most of these methods consider the case of global minutiae matching (alignment involved). In our work [61], we addressed this problem in presence of local minutiae descriptors, in particular the MCC, by introducing a new local quality measure, namely cylinder quality measure. We also proposed a quality-based consolidation approach, to embed this local quality measure into the MCC based matching (without need for alignment) in order to finally obtain better recognition rates.

3 Cylinder quality measures

The main idea in this chapter is to introduce a quality measure for modern local minutiae descriptors, particularly the MCC descriptors. Regarding the cylindrical structure of each MCC descriptor, such a local quality measure has been called cylinder quality measure by us [61].

3.1 Quality of local minutiae structures

Local minutiae structures are local descriptors encoding the relationship between each minutia and its neighboring minutiae usually in terms of rotation and translation invariant measures. Since each descriptor encodes the local information inside a fingerprint, a local quality assessment can be considered there as well. To the best of our knowledge, there is no quality measure specifically associated with the modern local minutiae structures, and in particular the MCC descriptors. Therefore, one of our primary goals in this thesis was to estimate a quality measure for each local minutiae structure based on the MCC, measuring its usefulness for global comparisons. Ideally, such a quality measure is supposed to quantify the degree to which an MCC descriptor is free of degradations known to harm the recognition performance. This measure can also be helpful to determine and possibly discard those descriptors that are likely to have a negative impact on the comparison performance.

To this end, we have taken the advantage of two closely related attributes of the fingerprint, and proposed the following main approaches for estimating cylinder quality measures:

1. Cylinder quality estimation using minutiae quality
2. Cylinder quality estimation using fingerprint quality maps

3.2 From minutia quality to cylinder quality

Minutia extraction is usually followed by a quality assessment for each candidate minutia point, for example to remove false minutiae. In the standard ISO/IEC 19794-2 [52], a standard template is specified for representing finger minutia data. In this standard template, there is a place left for the quality of each minutia in the range [0, 100]. However, there is no clear definition for minutia quality and it is left to be assigned by the suppliers. The value of 0 usually means "minutia quality is not assigned" and the lowest quality is represented by 1. Minutia reliability [112, 99], defined as probability of the extracted minutia being a valid minutia, has also been mentioned by different authors but it is usually considered as an intermediary measure for estimating the minutia quality. Minutia quality is probably the closest concept to the cylinder quality measure, since MCC descriptors mainly encode the local minutiae information. For example, a descriptor encoding the false minutiae is assumed to be of bad quality. Minutia quality is usually computed using one or a combination of the following approaches:

1. **No-Reference methods:** In such methods, local quality assessment of the fingerprint is usually performed in the minutia neighborhood to estimate minutia quality. The mean and standard deviation of pixel intensities in the neighborhood of each minutia are two commonly used features to estimate so-called minutia reliability. Such minutiae reliability is usually an interim measure which is combined with other local quality features to estimate final minutiae quality. For example in the MINDTCT package of the NBIS [109], it is assumed that a high quality neighborhood has a significant contrast that will cover the full gray-scale spectrum, based on which they have concluded that the pixel intensities of an ideal neighborhood must have a mean very close to 127 pixels and a standard deviation greater than 64 pixels for an image with 500 ppi resolution and pixel intensities in the range [0, 255]. More specifically, a minutia reliability measure, MR, is calculated as follows:

   $$MR = min\left(\left|1 - \frac{|\mu\text{-}127|}{127}\right|, \frac{\sigma}{64}, 1\right),$$

   where μ and σ are the mean and standard deviation of the pixel intensities in the minutia neighborhood respectively. The neighborhood is considered an area with the radius of 11 pixels around the corresponding minutia in this case. Then the minutia quality is computed by considering both the minutia reliability MR and the local quality LQ of the minutia location according to the 5-level MINDTCT quality map (refer to Section 3.5.7). The minutia quality, $\mathbf{MQ}_{\texttt{MINDTCT}}$, is computed in the range of 1 (lowest quality) to 99 (highest quality) as follows:

   $$\mathbf{MQ}_{\texttt{MINDTCT}} = \begin{cases} 49 \times MR + 50 & \text{if } LQ = 4 \\ 24 \times MR + 25 & \text{if } LQ = 3 \\ 14 \times MR + 10 & \text{if } LQ = 2 \\ 4 \times MR + 5 & \text{if } LQ = 1 \\ 1 & \text{if } LQ = 0 \end{cases} \tag{3.1}$$

   Other than the NBIS MINDTCT, we also used another well-known minutiae extractor called FingerJetFX [2] in many experiments to extract the minutiae and also the minutiae quality. FingerjetFX is originally developed in DigitalPersona[1], but its open source edition is freely available in [2]. The FingerjetFX minutiae quality are obtained by combining the responses of two in-house designed filter banks. More specifically, the local image around a given minutia candidate is firstly rotated such that the local ridge direction is perpendicular to x-axis. Given the rotated image around the minutia candidate, each filter bank provides 3×3 responses in 5 different scales. The response in each scale is calculated using 2D convolution of the rotated image with a 13×13 kernel specific to that scale. If all 45 response elements ($3 \times 3 \times 5$) from the k-th filter bank are denoted by $F_i^{(k)}, i = 1, 2, ..., 45, k = 1, 2$, then a confidence measure MC is computed for the minutia candidate as follows:

$$MC = \max_{1 \le i \le 45} \left(\max \left(w_i \cdot \left| F_i^{(1)} - F_i^{(2)} \right|, w_i \cdot \left| F_i^{(1)} + F_i^{(2)} \right| \right) \right), \tag{3.2}$$

where $w_i, i = 1, ..., 45$, is a set of fixed weights pre-defined in the software[2]. This confidence measure is normalized and expressed by an unsigned 8-bit integer in the range [0, 255]. Minutia quality $\mathbf{MQ}_{\texttt{FJFX}}$ is finally obtained by normalizing the confidence measure MC according to Eq. 3.3, and represented by an integer in the range from 1 (lowest quality) to 100 (highest quality).

$$\mathbf{MQ}_{\texttt{FJFX}} = \left\lceil min \left(\frac{MC + 1}{2}, 100 \right) \right\rceil. \tag{3.3}$$

It is worth mentioning that the minutiae quality provided by the FingerJetFX are selected among the candidate features for development of the NFIQ 2.0 [1].

Most of the existing algorithms for estimating the minutiae quality, including those considered in our experiments, are actually no-reference methods.

2. **Reference-Based methods:** Dictionary learning or correlation-based methods are used to estimate minutia quality based on some reference data, which is usually a patch of high quality minutia images selected beforehand. In the correlation-based approach, e.g. [27], firstly a set of high quality minutia images is selected manually. After image scaling, the candidate minutia image is rotated to several orientations and several scores are obtained by computing the correlation of each rotated image with each image in the high-quality minutiae set. The maximum score of all orientations would be chosen as the correlation score and the minutia quality is calculated as the average of the correlation scores with all high quality images inside the set. Dictionary learning has been also used in [114] for minutiae reliability assessment of latent fingerprints. Bayesian filtering is another approach proposed in [99] for minutia localization and quality assessment.

[1] This biometric company is now called Crossmatch after being acquired by Cross Match Holdings in 2014.

[2] Corresponding values of the weights w_i and the convolution matrices (13×13 kernels) of each filter bank can be viewed in the header file *biffilt.h* of the FingerJetFX software [2]

Similarly, we propose to consider a quality measure for local minutiae structures like MCC descriptors. As explained in Section 2.7, MCC is a minutiae descriptor taking into account a fixed-radius area around each minutia, therefore a cylinder quality measure can be obtained in the local region of a cylinder. One should note that unlike the minutia, the local regions corresponding to the cylinders overlap, thus being highly correlated especially where there are many minutiae close to each other. Another way to evaluate the cylinder quality can be combining the qualities of minutiae contributing to the cylinder. Since a minutiae template [52] contains mainly the information about minutiae (e.g., position, direction and possibly the quality of each minutia), employing minutia quality is helpful specially when we have access to the minutiae templates only (rather than fingerprint images). In this setting, we propose the cylinder quality measure to be estimated as weighted average of involving minutiae qualities.

Considering a cylinder C_m for the central minutia m, we denote by $\{m_i, i = 1, ..., N_{C_m}\}$ the set of all minutiae contributing to this cylinder, i.e., those within a fixed distance from the central minutia m (including m itself). Now assuming Q_{m_i} to be the quality of minutia m_i, a cylinder quality measure, Q_{C_m}, is proposed to be estimated as follows:

$$Q_{C_m} = \frac{\sum_{i=1}^{N_{C_m}} \left(w_{C_m|m_i} \cdot Q_{m_i} \right)}{\sum_{i=1}^{N_{C_m}} w_{C_m|m_i}}, \tag{3.4}$$

where $w_{C_m|m_i} = e^{-\frac{d_s^2(m_i,m)}{2\sigma_q^2}}$ is the relative contribution of minutia m_i to the cylinder quality measure, and $d_s(m_i, m)$ is the Euclidean distance between the locations of the minutia m_i and the central minutia m. Therefore, the highest weight is given to the central minutia and the weights are decreased exponentially for other minutiae according to their distance from the central minutia. The parameter σ_q determines the rate of decay and the denominator normalizes the weights such that they sum up to one, forcing Q_{C_m} to be in the same range as minutiae quality.

σ_q is an additional parameter which can be determined using some training data. Two extreme cases for σ_q can be interpreted as follows:

- **If** $\sigma \to 0$, the cylinder quality measure will be equal to the quality of central minutia in the cylinder.

- **If** $\sigma \to \infty$, the cylinder quality measure will be equal to the average of the qualities of all minutiae inside the cylinder.

However, based on our observations and several experiments (which are presented in next chapters, especially in Section 6.4), a smaller σ_q (with respect to the cylinder radius) is usually preferred for estimating cylinder quality measures. This is mainly due to the fact that the central minutia (and thus the central cylinder area) is of higher importance in each cylinder. We discuss this issue more closely in Section 3.6. Apart from that, another important fact in this regard is the considerable overlap between the cylinder areas within a fingerprint image. Very big σ_q (e.g., uniform weighting) in presence of huge overlaps results in a very similar cylinder quality measure for different descriptors, making them of rather no use.

It is worth mentioning that the cylinder quality measure, as well as minutia quality, can be added as auxiliary data to the fingerprint templates with no major additional cost and compliant with security requirement [54].

3.3 Estimation of cylinder quality measures from quality maps

A fingerprint image has varying levels of quality in different regions, meaning some local regions within the fingerprint are possibly more degraded than the others, thus having more negative impact on the recognition performance. Therefore, it is critical to locally analyze the quality of a fingerprint image. Local quality assessment of fingerprints is mainly based on the analysis of several local features of the fingerprints, for example the directional flow of the ridges (refer to Section 2.6.1). The information about local quality is often represented in a fingerprint quality map. In order to obtain the quality map for a given fingerprint image, the image is usually divided to several non-overlapping square blocks and a local quality measure is estimated for each block as presented in Section 2.6.1. An example fingerprint quality map can be viewed in Figure 3.1. The local areas corresponding to two possible cylinders are also shown in this figure to better illustrate why it is reasonable to assess the local quality within the area encoded by each descriptor. In this Section, we propose several approaches for estimating the cylinder quality measures directly from the quality maps.

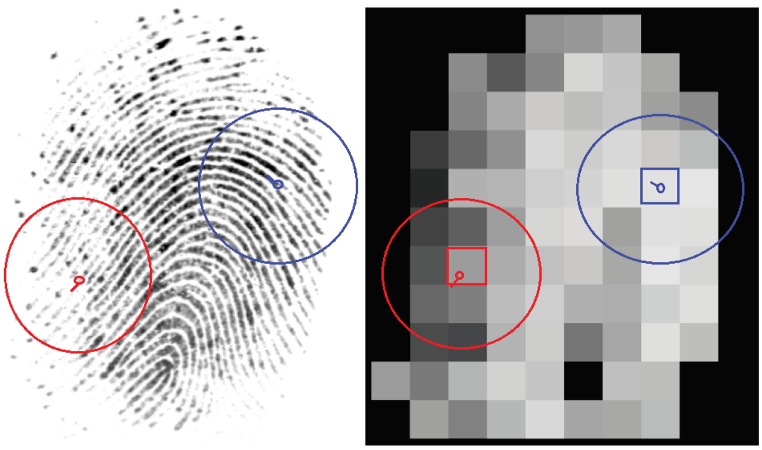


Figure 3.1 – Illustration of a fingerprint quality map having the blocks of 32 × 32 pixels, where brighter blocks represent higher quality. The areas corresponding to two cylinder examples are also shown, where the blue cylinder at the right side of the fingerprint is supposed to have better quality due to better clarity of the ridges in that region.

As explained in Section 3.3, minutiae quality are mostly estimated by some kind of local quality assessment within their neighborhood. Therefore, a reasonable approach is to use the quality map in order to first estimate the minutiae quality and then combine them into a cylinder quality measure according to Eq. 3.4. The quality of each minutia can be approximated by the quality of the block where it resides. Figure 3.2 illustrates such a configuration, highlighting those blocks containing minutiae.

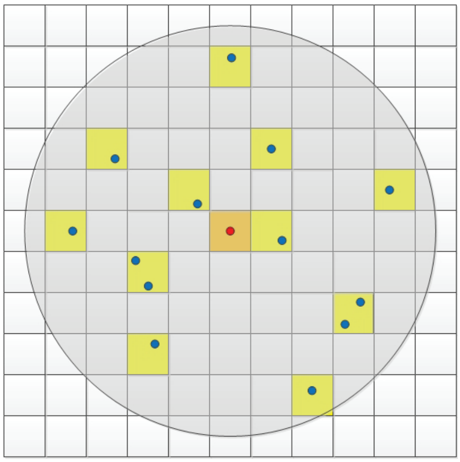


Figure 3.2 – 16 × 16 pixel blocks containing the minutiae considered for estimating the cylinder quality measure for a cylinder of radius 75 pixels.

Another approach is to consider the set of all blocks that approximately fall within the area of a given cylinder in order to estimate the cylinder quality. However, it is generally preferred to assess the quality within the areas where the extracted features exist.

3.4 Repositioned quality blocks for estimating cylinder quality

So far the local quality is assumed to be extracted from the standard fingerprint quality maps, particularly considering the blocks containing minutiae. In such a case, the estimation might not be so precise for those minutiae near the border of each block or even far from the center of each block. Therefore, an alternative approach would be to compute the local quality measure in the blocks centered at the position of each minutia. In other words, we can take into account a square block around each minutia and estimate the quality of that block using the local quality features of fingerprint image.

3.5 Candidate local quality features for cylinder quality measures

Regarding the ISO/IEC TR 29794-4 standard [56], specifying different finger image quality metrics, and based on the comprehensive reviews of existing fingerprint quality measures, specially in [6, 91], we found the following to be the main approaches for local quality assessment of fingerprint images, as well as high-resolution palmprint images:

1. Gabor Filters (GAB) [98, 90]
2. Orientation Certainty Level (OCL) [77]
3. Local Clarity Score (LCS) [28]
4. Frequency Domain Analysis (FDA) [78]
5. Orientation Flow (OF) [28]
6. Ridge Valley Uniformity (RVU) [77]
7. NBIS MINDTCT Quality Map [109, 108]
8. Ridge Clarity Map [115, 114]

These methods have been all introduced to obtain a global quality measure via an interim fingerprint quality map. But our aim in this thesis is to use the quality maps at local level in order to estimate the cylinder quality measures based on the method proposed in Section 3.3. In the following sections, these candidate quality maps are briefly described together with a fingerprint and a high-resolution palmprint example for each one.

3.5.1 Gabor Filters

Gabor filters are firstly used by Shen et al. [98] to obtain a global quality measure for fingerprint images. Their method is based on computing the Gabor filter responses for several directions at each block to classify them into so called "Good" and "Bad" blocks [98], but it does not explicitly provide a standard fingerprint quality map. Later in [90]Olsen et al. modified this method in order to be applicable for each pixel within the image, resulting in a full resolution quality map for each fingerprint image. This quality map is denoted by GAB.

To do so, firstly the fingerprint image is filtered using a 2D Gaussian kernel with $\sigma = 8$. The result is then subtracted from the original image. Considering several orientations $\theta = \frac{k-1}{n\pi}, k = 1, \dots, n$, the Gabor responses of the filtered image are computed for each direction as follows:

$$h_{cx}(x, y; f, \theta, \sigma_x, \sigma_y) = \exp\left(\frac{1}{2}\left(\frac{x_\theta^2}{\sigma_x^2} + \frac{y_\theta^2}{\sigma_y^2}\right) e^{j2\pi f x_\theta}\right),$$

where $x_\theta = x\sin\theta + y\cos\theta$, and $y_\theta = x\cos\theta - y\sin\theta$.

Then the magnitudes of the responses are convolved with a 2D Gaussian kernel with $\sigma = 6$, and finally the standard deviation of the Gabor magnitude response values at each pixel is computed, yielding a fingerprint quality map. The following parameters are usually used for 500 ppi images: $n = 4$, $f = 0.1$ and $\sigma_x = \sigma_y = 6$.

In Figure 3.3, the GAB quality map is shown for a fingerprint sample from the FVC2004 DB1 database and a palmprint image from THUPALMLAB database. All quality maps in this section are created for the same fingerprint and palmprint examples.

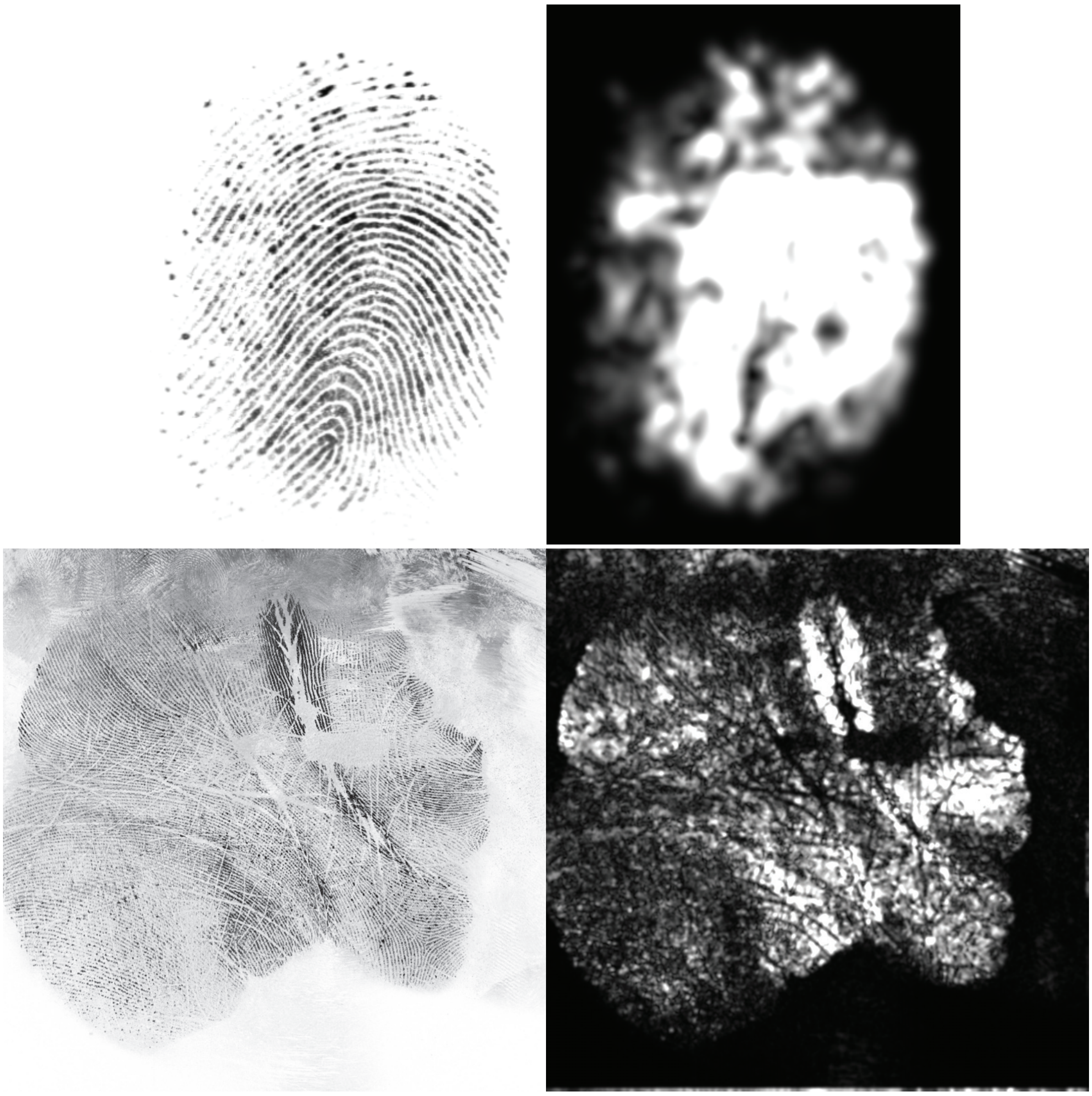


Figure 3.3 – Original fingerprint image (left above) and palmprint image (left below) and their corresponding GAB quality maps (right), where brighter blocks represent higher quality.

3.5.2 Orientation Certainty Level

The Orientation Certainty Level (OCL) [77] is computed from the covariance matrix of the intensity gradients dx and dy. These gradients are computed beforehand at each block using the 3 × 3 Sobel operators. The covariance matrix is calculated for a given block as follows [77]:

$$CovarianceMatrix = \frac{1}{N}\sum_{N}\left\{\begin{bmatrix} dx \\ dy \end{bmatrix}\begin{bmatrix} dx & dy \end{bmatrix}\right\} = \begin{bmatrix} a & c \\ c & d \end{bmatrix},$$

where N is the total number of pixels in the corresponding block.

The eigenvalues λ_{min} and λ_{max} computed from the covariance matrix are then used to calculate the OCL quality measure Q_{OCL}^{Block} of the corresponding block, as follows:

$$\lambda_{min} = \frac{a+b-\sqrt{(a-b)^2+4c^2}}{2},$$

$$\lambda_{max} = \frac{a+b+\sqrt{(a-b)^2+4c^2}}{2},$$

and

$$Q_{OCL}^{Block} = 1 - \frac{\lambda_{min}}{\lambda_{max}}.$$

In Figure 3.4, the OCL quality map is shown for a fingerprint and a palmprint example.

3.5.3 Local Clarity Score

In order to obtain the Local Clarity Score (LCS) [28] measure for each block of size 32×32 pixels, the block needs to be rotated until its dominant ridge orientation line is parallel to y-axis. Then a new rectangular block $B_2(i, j)$ (usually with the height of M =13 pixels) is extracted at the center of the orientation line. This 2D block is averaged along the y-axis to obtain a 1D vector $B_3(i) = \frac{1}{M}\sum_{j=1}^{M} B_2(i, j)$.

By applying linear regression on B_3, a threshold on the intensity values can be determined for ridge valley separation. This threshold is used then to determine the proportion of misclassified pixels in the block $B_2(i, j)$. The proportion of misclassified pixels in the valley and ridge regions are denoted by α and β respectively.

If we consider S to be the scanner resolution (e.g., S = 500 ppi), the normalized ridge width $\overline{W_r}$ and the normalized valley width ($\overline{W_v}$) can be estimated like this:

$$\overline{W_v} = \frac{W_v}{\left(\frac{S}{500}\right) W_{500}^{max}},$$

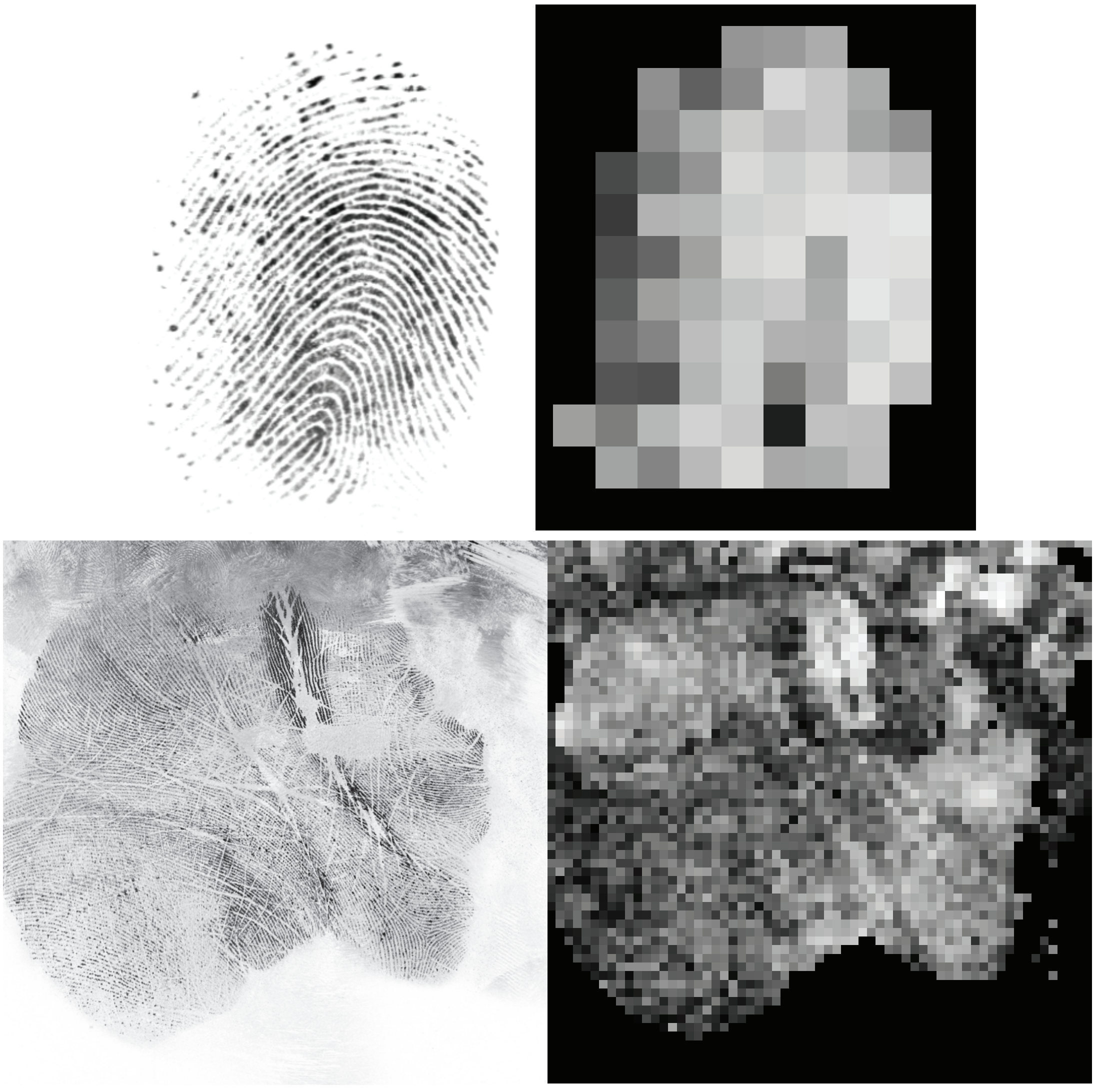


Figure 3.4 – Original fingerprint image (left above) and palmprint image (left below) and their corresponding OCL quality maps (right), where brighter blocks represent higher quality.

$$\overline{W_r} = \frac{W_r}{\left(\frac{S}{500}\right) W_{500}^{max}},$$

where W_{500}^{Max} is the estimated maximum ridge and valley width for an image with resolution of 500 ppi. W_{500}^{Max} is usually assumed to be around 20 pixels.

Finally the Local Clarity Score for the given block is computed as follows:

$$Q_{LCS}^{Block} = \begin{cases} 1 - \frac{(\alpha+\beta)}{2} & \left(W_v^{min} < \overline{W_v} < W_v^{max}\right) \wedge \left(W_r^{min} < \overline{W_r} < W_r^{max}\right) \\ 0 & otherwise \end{cases},$$

where W_v^{max} and W_r^{max} are the maximum values for normalized valley and ridge width, and

W_v^{min} and W_r^{min} are the corresponding minimum values. In Figure 3.5, the LCS quality map is shown for a fingerprint and a palmprint example.

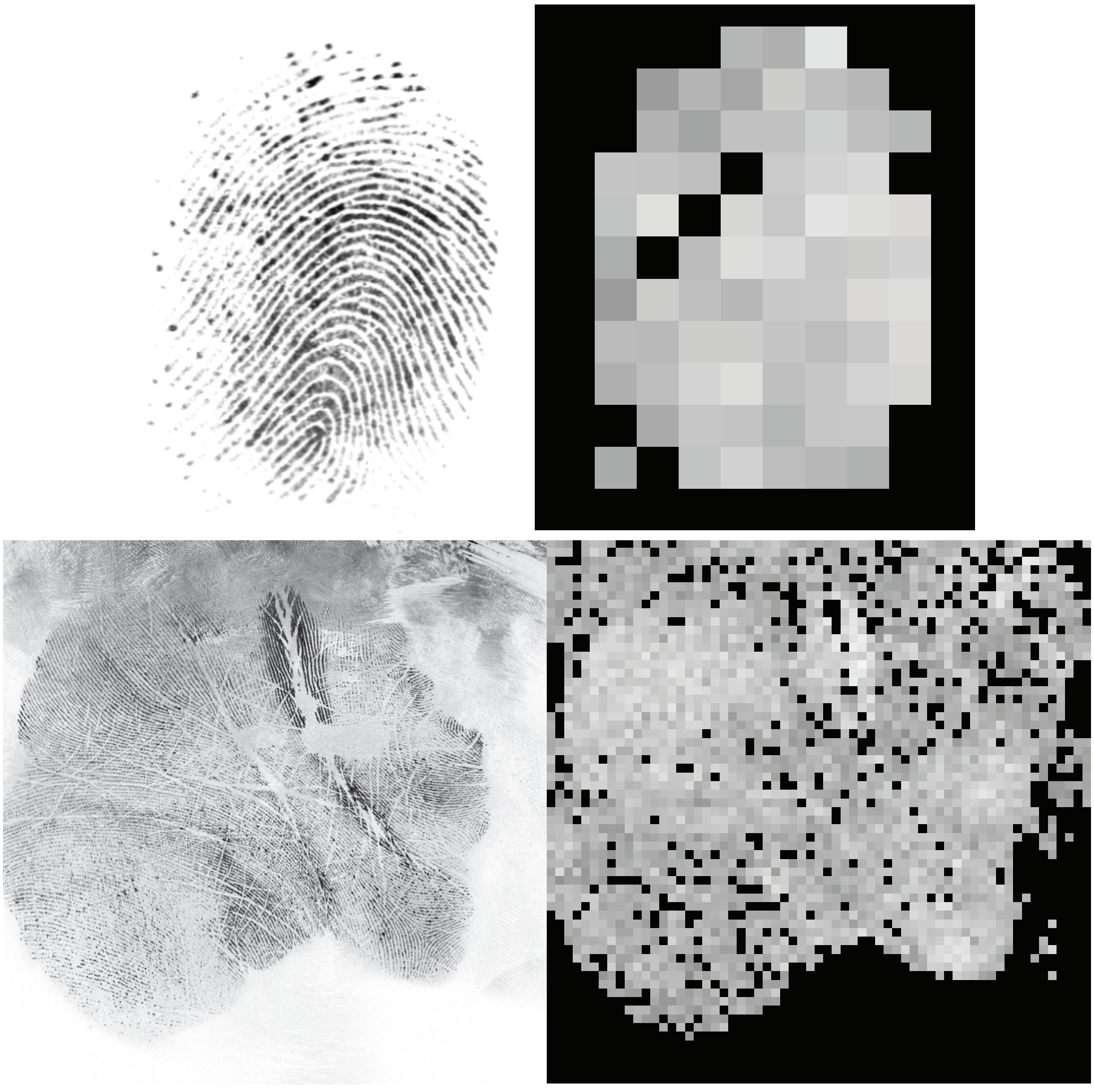


Figure 3.5 – Original fingerprint image (left above) and palmprint image (left below) and their corresponding LCS quality maps (right), where brighter blocks represent higher quality.

3.5.4 Frequency Domain Analysis

Frequency Domain Analysis (FDA) is proposed to estimate a local quality measure based on analysis of Discrete Fourier Transform (DFT) of the blocks within the fingerprint image. We first need to determine the dominant ridge flow in the block and rotate the block so that the x-axis is perpendicular to the dominant ridge flow. After cropping the central region, we compute a so-called ridge-valley signature $T(x)$ as follows:

$$T(x) = \frac{1}{2r+1}\sum_{j=-r}^{r} I(x,j).$$

Then assuming $A(F)$ to be the DFT magnitude of the signature $T(x)$, i.e., $A(F) = |\mathscr{F}\{T(x)\}|$, $F \in \{0,1,...,N-1\}$, we can obtain the quality measure of the corresponding block Q_{FDA}^{Block} as follows:

$$F_{max} = \underset{F>0}{argmax} A(F),$$

$$Q_{FDA}^{Block} = \frac{A(F_{max}) + 0.3\,(A(F_{max}-1) + A(F_{max}+1))}{\sum\limits_{F=1}^{N/2} A(F)}.$$

In Figure 3.6, the FDA quality map is shown for a fingerprint and a palmprint example.

3.5.5 Orientation Flow

Orientation Flow (OF) quality measure is based on computing the absolute orientation difference between a block and its neighboring blocks [28].

For each block (i,j) in the image, we first need to determine the dominant ridge orientation, denoted by $DRO(i,j)$. Then we compute the absolute orientation difference (AOD) between the underlying block and its neighboring blocks, as follows:

$$AOD = \frac{\sum_{m=-1}^{1}\sum_{n=-1}^{1} |DRO(i,j) - DRO(i-m,j-n)|}{8},$$

$$Q_{OF}^{Block} = \begin{cases} 1 - \frac{AOD-\theta_{min}}{90-\theta_{min}} & AOD > \theta_{min} \\ 1 & AOD \le \theta_{min} \end{cases},$$

where θ_{min} is the threshold for the minimum angular change in the orientation flow, which can be considered 0 leaving no tolerance on that. All angles are in degrees here.

In Figure 3.7, the OF quality map is shown for a fingerprint and a palmprint example.

3.5.6 Ridge Valley Uniformity

Ridge Valley Uniformity (RVU) is designed to measure the coherency of the ridge to valley width ratio within a block. Computing the RVU begins with the same procedure as the LCS,

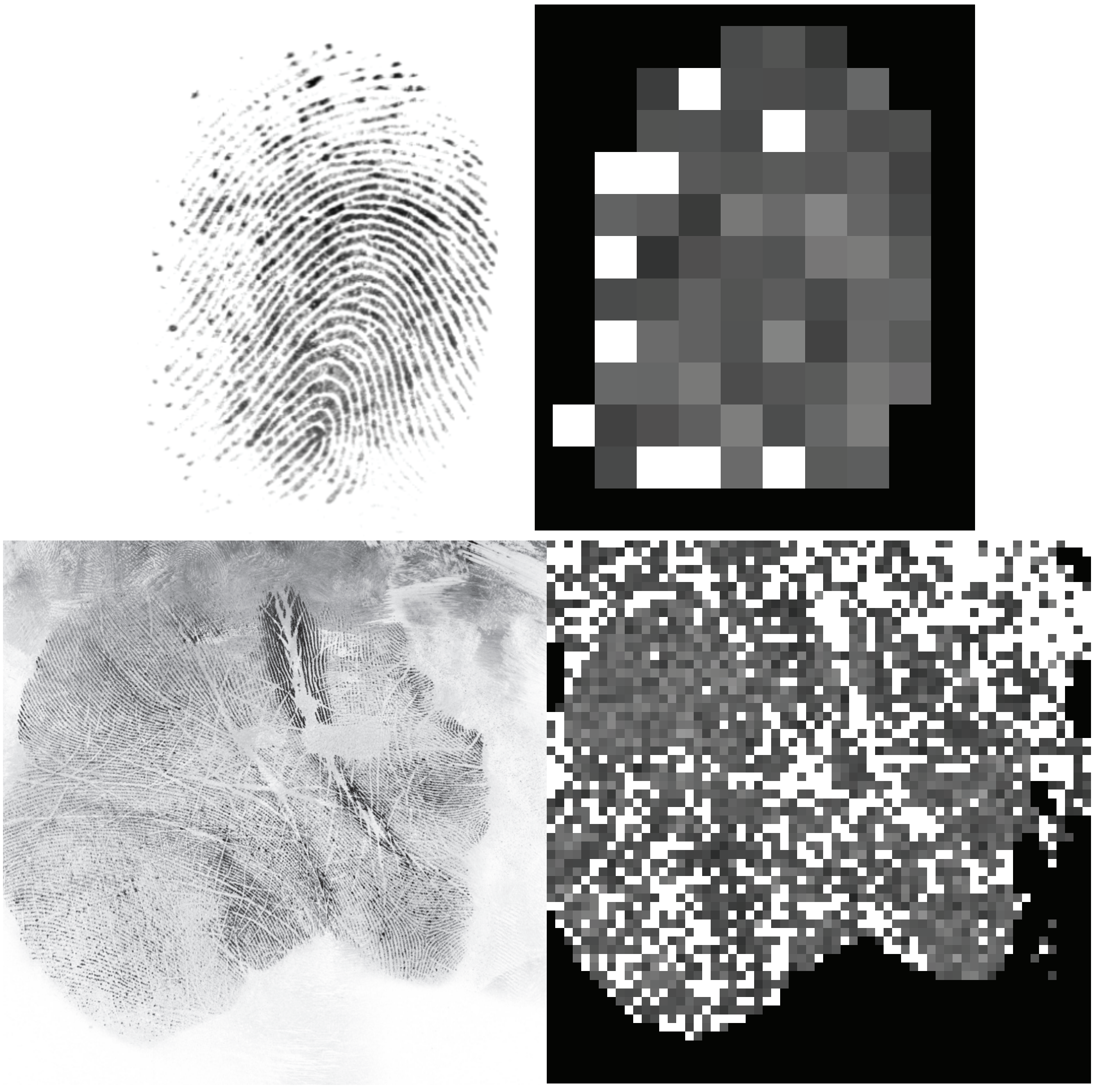


Figure 3.6 – Original fingerprint image (left above) and palmprint image (left below) and their corresponding FDA quality maps (right), where brighter blocks represent higher quality.

but after determining the threshold by linear regression, several indexes in the first and last part of B_3 are removed in order to get rid of incomplete ridges and valleys at the borders of the underlying block. Finally the block RVU Q_{RVU}^{Block} is obtained by calculating the ridge to valley thickness ratio for the remaining part. In Figure 3.8, the RVU quality map is shown for a fingerprint and a palmprint example.

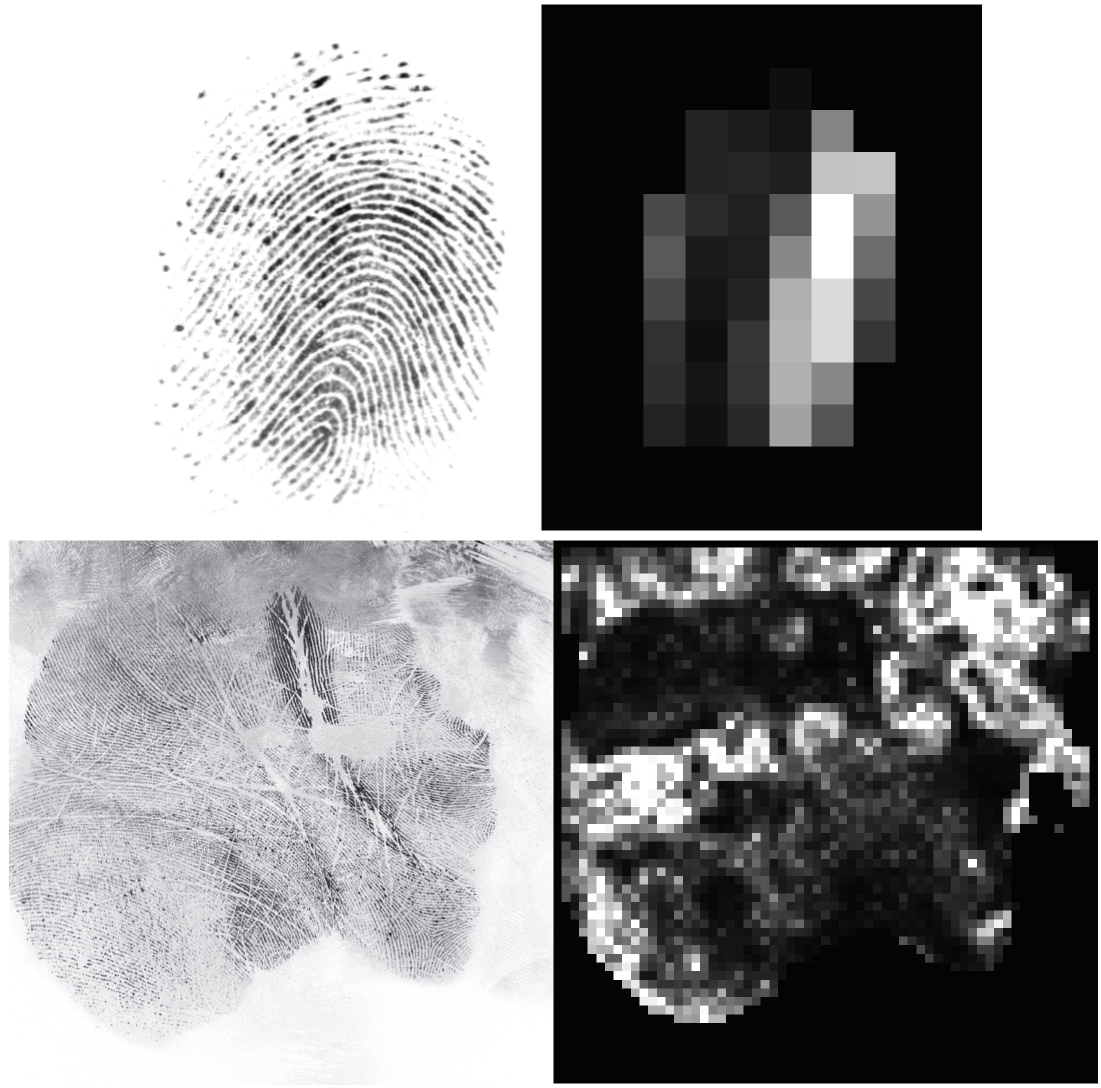


Figure 3.7 – Original fingerprint image (left above) and palmprint image (left below) and their corresponding OF quality maps (right), where brighter blocks represent higher quality.

3.5.7 NBIS MINDTCT Quality Map

The minutia detection package MINDTCT of the NBIS [108, 109], provides a fingerprint quality map via heuristic combination of the following four maps:

1. **Direction Map:** The map represents the direction of ridge flow for the 8 × 8 pixel square blocks within the fingerprint image. If a valid ridge flow could not be determined for a block, its value is set to -1, otherwise the ridge flow direction of the block is quantized into 16 equally spaced levels over a semicircle.

2. **High-Curvature Map:** A map of binary values with the same dimension as the Direction Map, where the blocks with value of 1 have normally a high-curvature ridge flow (for

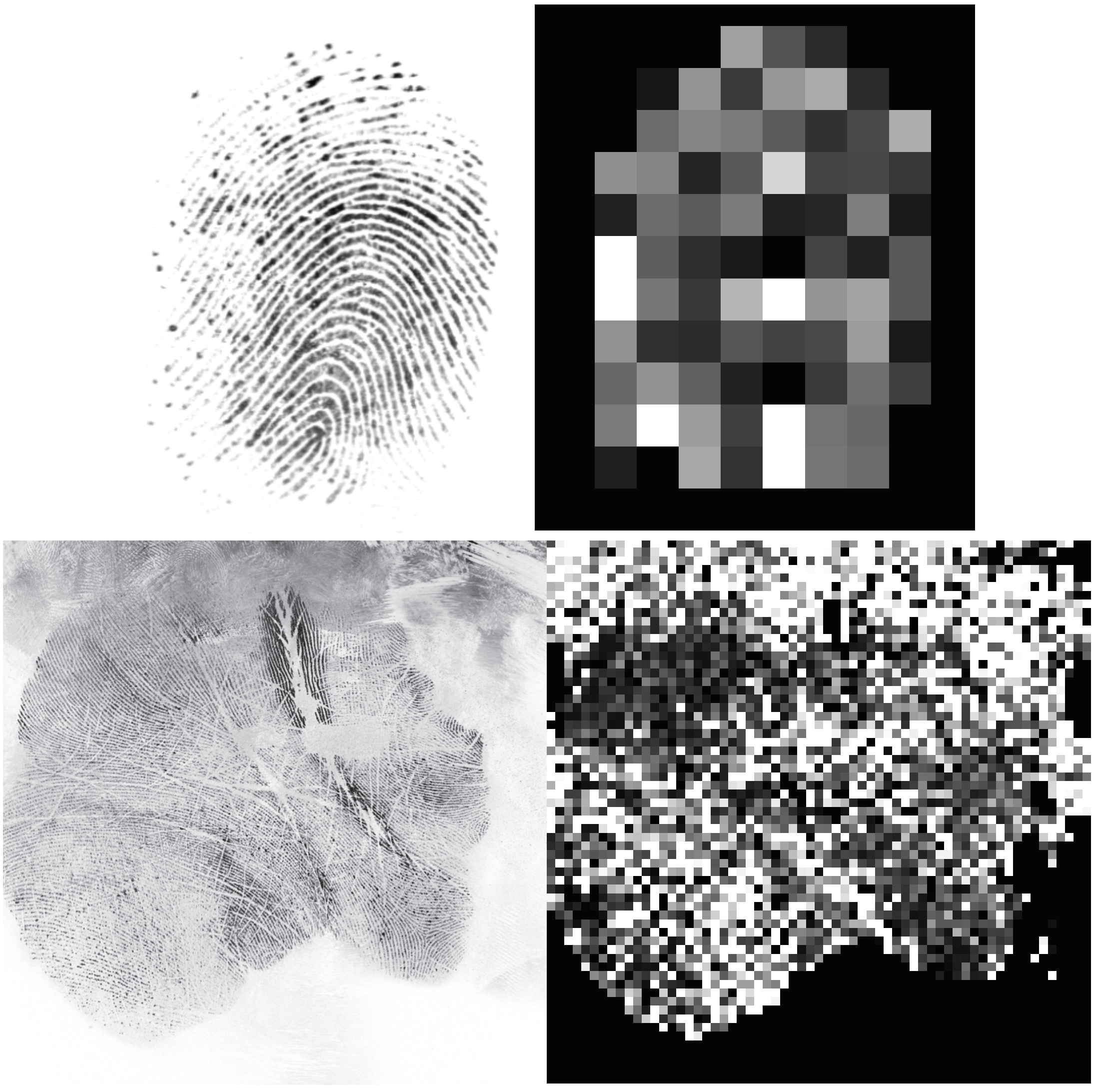


Figure 3.8 – Original fingerprint image (left above) and palmprint image (left below) and their corresponding RVU quality maps (right), where brighter blocks represent higher quality.

examples regions close to the core and delta of the fingerprint).

3. **Low-Contrast Map:** It is a binary map with the same dimension as the Direction Map (8 × 8 pixel blocks), where the blocks with value of 1 are located within a low-contrast area. The low-contrast area usually represent the background in the fingerprint image.

4. **Low-Flow Map:** A binary map of the same size with the value of 1 belonging to the blocks where a dominant directional frequency could not be found.

This quality map outputs a local quality measure for each 8×8 pixel block within the fingerprint image in 5 integer levels from 0 to 4, where 4 represents highest quality and 0 represents lowest quality. This Quality Map is then used for estimating the quality of each minutia and for obtaining the NFIQ global quality measure [102]. In Figure 3.9, the MINDTCT quality map is shown for a palmprint sample from the THUPALMLAB database.

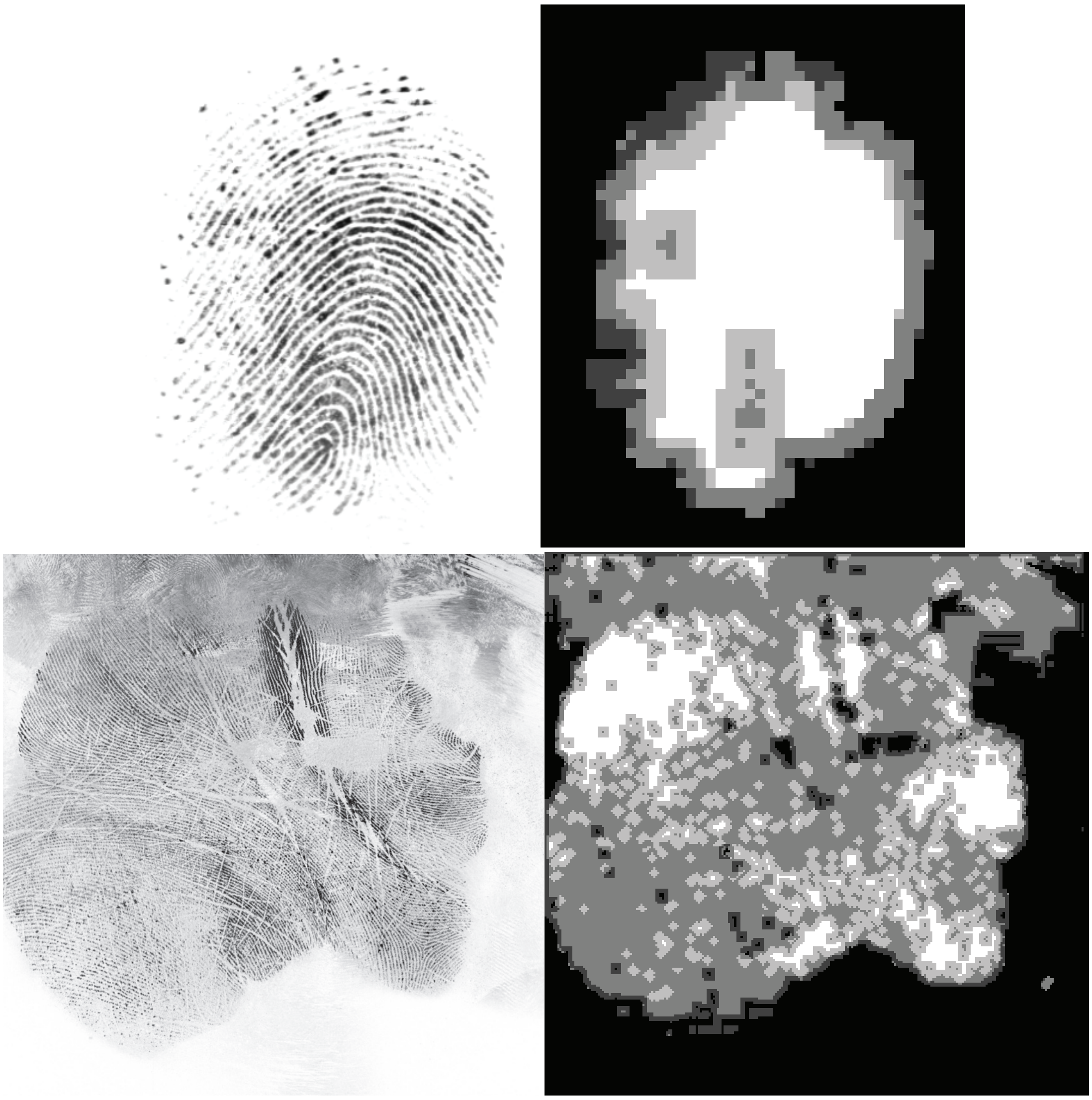


Figure 3.9 – Original fingerprint image (left above) and palmprint image (left below) and their corresponding MINDTCT quality maps (right), where brighter blocks represent higher quality.

The usual size of quality blocks (in pixels) is given in Table 3.1 for all the local quality measures mentioned above. The same size is used for generating all the quality maps shown earlier in this Section.

Quality map	Block size in pixels
OCL	32x32
LCS	32x32
OF	32x32
FDA	32x32
RVU	32x32
MINDTCT	8x8
GAB	1x1

Table 3.1 – The usual block size of the fingerprint quality map for different local quality features

3.5.8 Ridge Clarity Map for latent prints

In [115], Yoon et al. proposed an objective procedure to estimate the global quality of latent fingerprints. This global quality measure is obtained by combining two main features; the number of marked minutiae and the average ridge clarity in the convex hull of all minutiae. The local ridge clarity is estimated via an interim quality map called Ridge Clarity Map, which is proposed to be estimated via the following procedure: After contrast enhancement of the original latent image I, the resulting image I_* is partitioned into non-overlapping square blocks of size 16×16 pixels, and the following three steps are performed sequentially for each block.

1. **Fourier analysis:** Firstly a sub-image $I_*^{[b]}(x,y)$ of size 64×64 pixels is constructed for each block $[b]$. This is done by taking 32×32 pixels from I_* around the center of the block, and padding with zeros up to the final size of 64×64 pixels. Using 2D Fast Fourier Transform (FFT), the sub-image $I_*^{[b]}(x,y)$ is transformed to Fourier domain $F^{[b]}(u,v)$. Consequently, the top two local maxima of the amplitude $\left|F^{[b]}(u,v)\right|$ are chosen within the frequency range $[\frac{1}{16}, \frac{1}{5}]$ [29]. If we consider (u_i, v_i) as the location of the i-th maximum, the corresponding 2D sinusoidal waves for this block are estimated as follows:
   $w_i^{[b]}(x,y) = a_i^{[b]} \cdot \sin\left(2\pi f_i^{[b]}\left(x \cdot \cos\theta_i^{[b]} + y \cdot \sin\theta_i^{[b]}\right) + \phi_i^{[b]}\right),\ i = 1,2,$
   where $a_i^{[b]} = \left|F^{[b]}(u_i, v_i)\right|,\ f_i^{[b]} = \frac{\sqrt{u_i^2+v_i^2}}{64},\ \theta_i^{[b]} = \arctan\left(\frac{u_i}{v_i}\right), \phi_i^{[b]} = \arctan\left(\frac{Im[F^{[b]}(u_i,v_i)]}{Re[F^{[b]}(u_i,v_i)]}\right).$
2. **Ridge continuity estimation:** The ridge continuity for the block $[b]$ is estimated based on the continuity of the corresponding sinusoidal waves. Two sinusoidal waves $w^{[b_1]}$ and $w^{[b_2]}$ from two neighboring blocks $[b_1]$ and $[b_2]$ are assumed to be continuous, if:
   $\min\left(\left|\theta^{[b_1]} - \theta^{[b_2]}\right|, \pi - \left|\theta^{[b_1]} - \theta^{[b_2]}\right|\right) \le \frac{\pi}{10}$, and $\left|\frac{1}{f^{[b_1]}} - \frac{1}{f^{[b_2]}}\right| \le 6$, and
   $\sum_{(x,y)\in\mathscr{L}} \left|\frac{w^{[b_1]}(x,y)}{a^{[b_1]}} - \frac{w^{[b_2]}(x,y)}{a^{[b_2]}}\right| \le 3,$
   where $\mathscr{L}$ is the set of 16 pixels at the shared border of the two neighboring blocks.

   The ridge continuity for each block is estimated based on the number of adjacent blocks having continuous sinusoidal waves, as follows:

$Continuity^{[b]} = \sum_{j=1}^{8} \max\left(I_c\left(w_1^{[b]}, w_1^{[nb_j]}\right), I_c\left(w_1^{[b]}, w_2^{[nb_j]}\right)\right),$

where $\{[nb_1], [nb_2], ..., [nb_8]\}$ is the set of 8 neighboring blocks of the block $[b]$, and

$I_c\left(w^{[b_1]}, w^{[b_2]}\right) = \begin{cases} 1, & \text{if } w^{[b_1]} \text{ and } w^{[b_2]} \text{ are continuous,} \\ 0, & \text{otherwise.} \end{cases}$

3. **Ridge clarity estimation:** For each block $[b]$, the ridge clarity is obtained as follows:
   $RidgeClarity^{[b]} = a_1^{[b]} \cdot Continuity^{[b]}.$

Such a Ridge Clarity Map is shown in Figure 3.10 for a latent fingerprint example from NIST SD27 database [89].

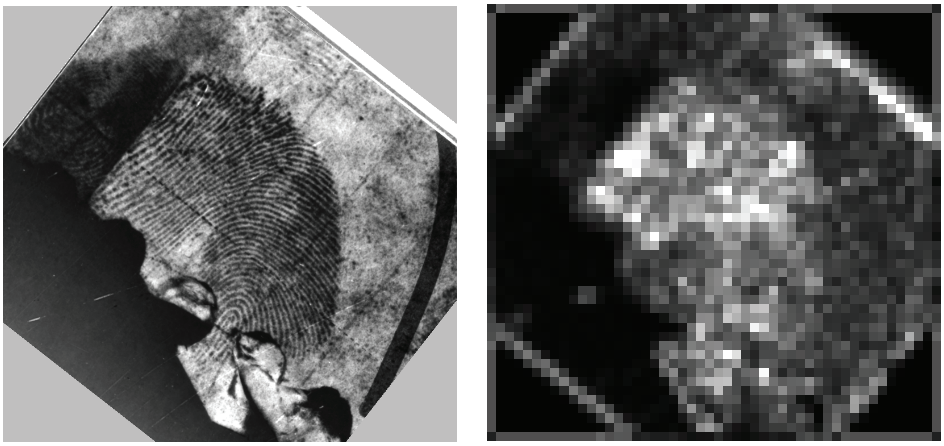


Figure 3.10 – Ridge Clarity Map (right) for a latent print (left) from the NIST SD27.

3.6 Importance of the cylinder central area

A phenomenon consistently observed in our experiments was that the quality of cylinder central area has more influence on the recognition performance than the areas far from the center.

One of the main reasons for this phenomenon is the fact that the central minutia plays more significant role in cylinder creation, in several ways such as:

1. Most importantly, the center and orientation of the coordination system for each descriptor is determined by the location and direction of the central minutia respectively.
2. The spatial contribution of all other minutiae within each cylinder depends on the central minutia location.
3. The directional contribution of all other minutiae within each descriptor depends on the central minutia direction.

No other minutia in the cylinder has such a privilege, hence it is reasonable to conclude that the central minutia must have a major contribution in cylinder quality measure as well. To understand it better, one can imagine only a wrong direction for the central minutiae, which can change the coordinate system of the MCC descriptor significantly, thus affecting the relative position of the elements in linearized descriptor. It can make serious errors in local similarity scores when the descriptor is compared against other descriptors. Therefore, the accuracy of the location and direction of central minutia is of high importance when it comes to estimating the cylinder quality measures.

3.7 Rotation invariance of cylinder quality measures

Other than rotation invariant features, central minutia direction also plays a significant role in rotation invariance of the MCC descriptors, since the orientation of the coordinate system for each descriptor is aligned solely according to this direction (Figure 3.11).

Concerning cylinder quality measures, as explained in Section 3.5, most of the existing methods for block-based local quality estimation of fingerprint image begin first with rotating the block according to the dominant ridge orientation within that block, then the central area of the rotated block is cropped for the quality estimation. This explains why most of the local quality features of fingerprint images are rotation invariant. In other words, we can expect to obtain approximately the same value for the local quality by rotating quality blocks as far as the size of blocks allow.

Moreover, the central minutia direction is highly correlated with the dominant ridge orientation in the central area of each cylinder, which is also consistent with the rotation invariant nature of MCC descriptors and cylinder quality measures, especially those which are mainly based on the quality of the cylinder central area.

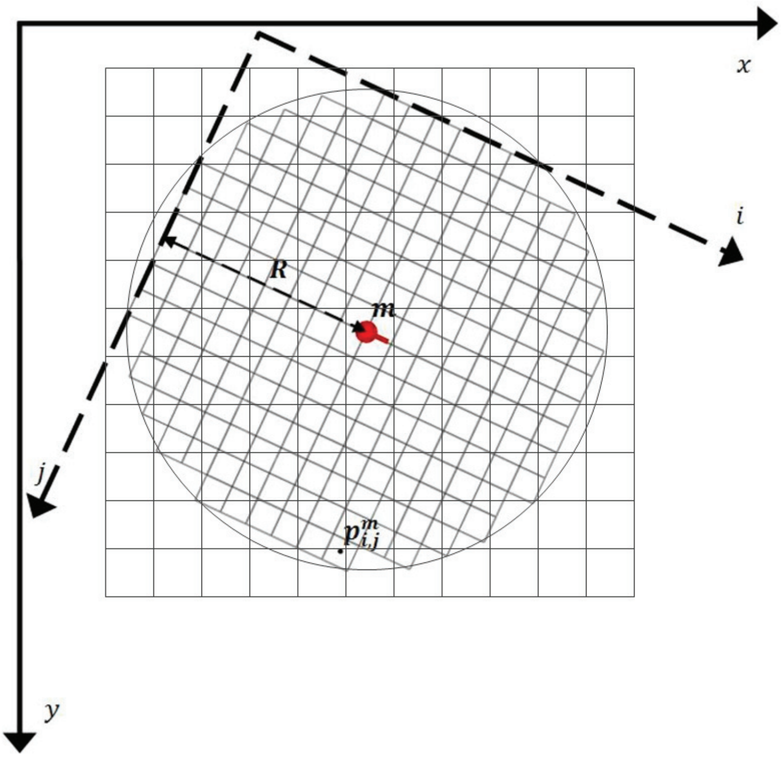


Figure 3.11 – Coordinate system of MCC descriptor (i, j) compared with the coordinate system of corresponding fingerprint quality map (x, y). [18]

4 Embedding local quality measures in MCC based comparison

In this chapter, we propose two approaches for embedding local quality measures, such as minutiae quality or cylinder quality measures, in MCC based comparison methods.

MCC based comparison, like many other minutiae-based comparison methods, involves local comparison and consolidation stages in its complete form, as shown in Figure 4.1. During local comparison, the MCC descriptors from two templates are compared, resulting in a matrix containing a local similarity score for every possible MCC pair from the two fingerprints. This matrix is usually called local similarity matrix, as displayed in Figure 4.1. By consolidation, we mean the process which starts at the level of local similarity scores and finishes by providing a global similarity score between the two templates. However, the term consolidation is usually used when the process needs other information (than just local similarity scores) such as original minutiae information to produce a global score by considering the global relationships among the pairs as well. With this definition, the simplest comparison methods which are based only on the local similarity scores and do not involve any consolidation step. The recognition performance is generally improved after a consolidation step. To make the long story short, we propose two different approaches for embedding local quality measures in this setting, as follow:

1. Discarding low-quality elements from local similarity matrix
2. Quality-based consolidation of local similarity scores

The first approach is at the level of local comparisons and is based on our recently published work [59]. The second approach is combined with a consolidation process, as proposed by us in [61]. We also propose a third approach, which is a supervised model trained to modify the local similarity score based on local quality measures. In this Chapter, we focus on the two approaches mentioned above and discuss the third one later in Chapter 5. It is worth mentioning that these three approaches could be also combined for better performance, since they are operating in different levels.

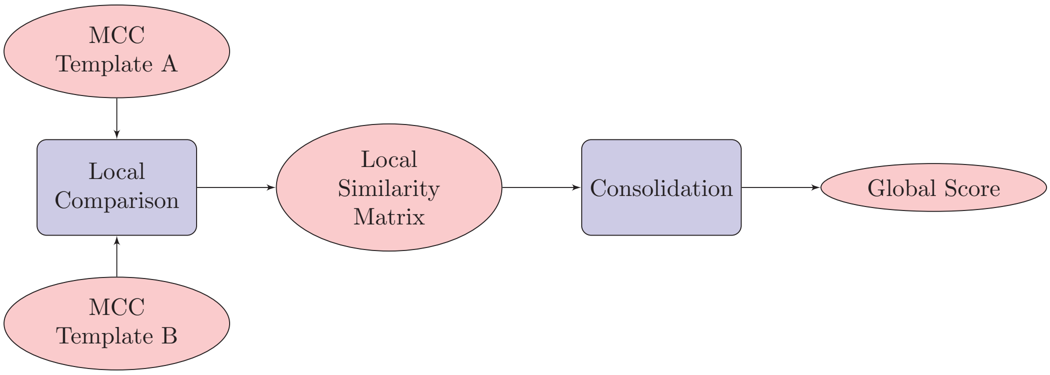


Figure 4.1 – Main levels in MCC based fingerprint comparison.

4.1 Discarding low-quality elements from local similarity matrix

In this section, we focus on discarding approach as a well-known methodology for embedding quality measures into biometric recognition systems. This approach is based on the fact that a part of biometric data (samples, regions, ...) with lowest quality can be discarded to improve the overall comparison accuracy. There are thresholds needed to be set for discarding criteria. It can be for example an absolute threshold on the value of corresponding quality measures, or the percentage of low quality data to be discarded. Difficulty in setting universal discarding thresholds makes this approach challenging as an embedding technique. Another important application of this approach is to evaluate and compare different quality measures in terms of their usefulness as a discarding criterion.

Almost at any stage of MCC based comparison, a discarding method can be applied. For example:

1. Some low-quality minutiae can be discarded from minutiae templates.
2. Some low-quality descriptors can be discarded from MCC templates.
3. Some low-quality MCC pairs can be discarded from local similarity matrix.

Other discarding scenarios can be considered depending on the global comparison method being used. From the possible approaches listed above, the first one is usually performed early during the minutiae extraction process in almost any minutiae extractor. In this section, we focus on a discarding approach after the MCC template creation, where it is assumed that all the minutiae have already contributed to the creation of MCC descriptors. Therefore, we address the second and the third approach listed above, where low-quality MCC pairs are chosen to be discarded from local similarity matrix based on their pairwise quality measures (the third approach) or independently (the second approach). Other than performance improvement, we also aim at designing a baseline algorithm for evaluating local quality features within the MCC based comparison framework.

Assuming a local similarity matrix Γ of size $n_A \times n_B$, and a given percentage $(100 \cdot \alpha)$ of the MCC pairs to be discarded from Γ, we can consider the following discarding scenarios:

1. ***Discarding independently:*** We discard $round(n_A \times \sqrt{\alpha})$ rows and $round(n_B \times \sqrt{\alpha})$ columns entirely from the matrix Γ. These rows and columns are corresponding to the descriptors having the lowest quality in each template independent of the other one. $round(x)$ is a rounding operator which returns the nearest integer to x.

2. ***Discarding based on pairwise quality measures:*** We discard the $round(n_A \times n_B \times \alpha)$ elements from the matrix Γ, corresponding to those MCC pairs having the lowest pairwise quality based on some pairwise function such as square root or minimum.

Discarding elements from local similarity matrix means to replace them with zero. In other words, the local similarity matrix will be multiplied element-wise with a $n_A \times n_B$ binary mask which is zero where the elements are going to be discarded, and one elsewhere.

4.1.1 Experimental setting

Databases: For our evaluations, we have chosen three FVC databases which are captured by different types of sensors: FVC2002_DB2 (optical sensor), FVC2002_DB3 (capacitive sensor) and FVC2004_DB3 (thermal sweeping sensor). Each database contains 800 fingerprint images, including 100 different fingers and 8 samples for each finger. Each sample is compared against the remaining samples of the same finger, creating 2800 genuine pairs, and the first sample of each finger is compared to the first sample of the remaining fingers, providing 4950 impostor pairs for each database [24].

Minutiae extraction: The open source minutiae extractor FingerJetFX is used to extract minutiae for all fingerprints.

Cylinder quality measures: As mentioned in Section 3.2, the FingerJetFX also provides a quality value for each minutia according to Eqs 3.2 and 3.3. It keeps by default only those minutiae having quality above 40 (out of 100) up to maximum 68 minutiae for each fingerprint. In all discarding experiments in this chapter, we use minutiae quality provided by the FingerJetFX to estimate cylinder quality measures. Later in Chapter 6, we evaluate some other quality measures using the discarding approach proposed here.

MCC parameters: Table 4.1 summarizes all parameters used for MCC template creation and comparison, which have been set according to the parameters published in [21].

MCC template creation and comparison: The publicly available MCC SDK Version 1.4 has been used to create the bit-based MCC descriptors (MCC16b). The Local Greedy Similarity (LGS) method [21] is applied for global comparison using the SDK in all cases. Therefore, the global score is directly computed from the local similarity matrix, without any iterative relaxation.

Table 4.1 – MCC parameters used for fingerprint experiments

(a) Cylinder creation

Parameter	Value
R	75
N_S	16
N_D	5
σ_S	6
σ_D	$\frac{5}{36}\pi$
μ_Ψ, τ_Ψ	$\frac{1}{200}, 400$
Ω	75
min_{VC}	0.2
min_M	1

(b) Comparison (matching)

Parameter	Value
min_{ME}	0.2
δ_θ	$\frac{2\pi}{3}$
μ_P, τ_P	$30, \frac{2}{5}$
min_{np}, max_{np}	3, 10
w_R	0.3
μ_1^ρ, τ_1^ρ	$\frac{1}{30}, -150$
μ_2^ρ, τ_2^ρ	$\frac{\pi}{4}, -15$
μ_3^ρ, τ_3^ρ	$\frac{\pi}{18}, -40$
n_{rel}	3

4.1.2 Cylinder quality: average vs. central minutiae quality

In [61], the cylinder quality measures have been proposed based on a weighted average of minutiae qualities inside cylinders, with bigger weights given to the minutiae close to the center. Here we consider two extreme cases of such cylinder quality measures: 1) a simple average of minutiae qualities inside each descriptor, 2) only the quality of central minutia in each descriptor. The Equal Error Rate (EER) has been evaluated on all three databases for different percentages of MCC pairs discarded independently. The results are shown in Figure 4.2. One can interpret from this figure that the central minutia quality is more efficient than the average minutiae quality to be used in the proposed approach, especially for higher discarding percentages. This could be due to the overlap between the cylinder areas within the fingerprint image.

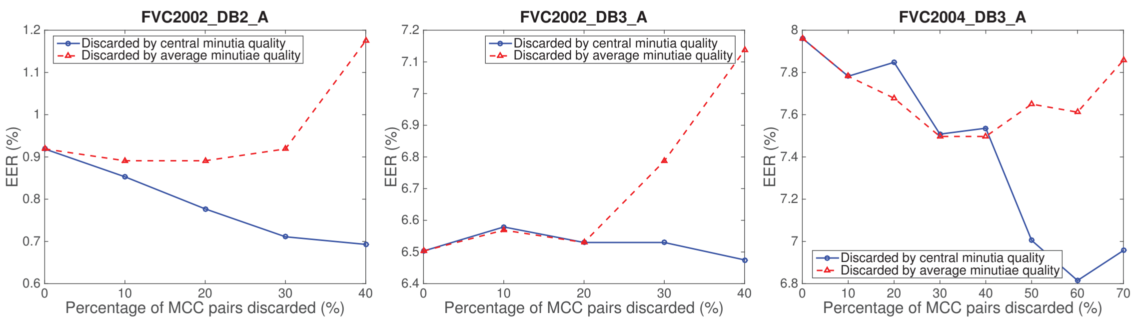


Figure 4.2 – EER vs. percentage of MCC pairs discarded based on central minutia quality (solid line) and based on average minutiae quality (dashed line).

4.1.3 Evaluations

Following the results presented in Section 4.1.2, we assume cylinder quality measure here to be the quality of its central minutia. Given two MCC descriptors with cylinder quality measures

Q_a and Q_b, we consider two common pairwise measures for our experiments: $\sqrt{Q_a \times Q_b}$ and $min(Q_a, Q_b)$. The Equal Error Rate (EER) has been evaluated on each database for different percentages of MCC pairs discarded from local similarity matrix via the methods proposed in Section 4.1, i.e., (1) discarding MCC pairs independently (independent discarding of rows and columns from local similarity matrix), (2) discarding of MCC pairs based on the pairwise quality $\sqrt{Q_a \times Q_b}$, and (3) discarding of MCC pairs based on the pairwise quality $min(Q_a, Q_b)$. The results given in Figure 4.3 show that all the methods improve the global verification performance to some extent after discarding a portion of low-quality MCC pairs. The performance improvement differs for different methods depending on the database and the percentage of discarding. The independent discarding of MCC pairs performs equally well or even better in some cases than the pairwise methods, with minimum function outperforming the square root function most of the times.

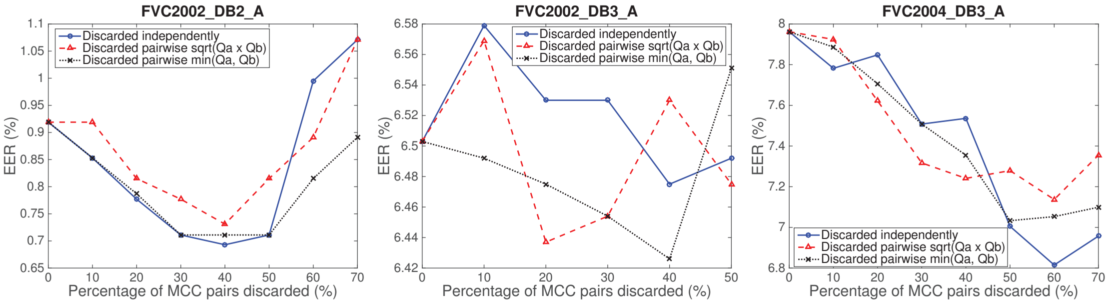


Figure 4.3 – EER vs. percentage of MCC pairs discarded independently (solid line), discarded using pairwise quality-square root (dashed line) and discarded using pairwise quality-minimum (dotted line).

4.1.4 Discussion

In Figure 4.3, it is shown that the proposed discarding method performs much better for FVC2004_DB3 than FVC2002_DB3 for example. A main reason for that is the fact that the average number of minutiae extracted for each fingerprint in FVC2004_DB3 is higher (almost double that of FVC2002_DB3), as seen in Table 4.2. Moreover, there are several fingerprints in FVC2002_DB3 with only a few minutiae, while there is no fingerprint with less than 19 minutiae in the FVC 2004_DB3. Discarding a fixed portion of elements may not be helpful in such cases, where very few minutiae are available in the fingerprints.[1] If we look at the distribution of minutiae qualities for each database, as shown in Figure 4.4, we see clear differences among them. For example, the distribution for the FVC2004_DB3 database shows that only a small portion of minutiae have very low quality (e.g., less than 50), comparing to the FVC2002_DB3 database with relatively a much higher portion of such low quality minutiae.

Discarding a fixed percentage of the lowest-quality elements might be a good choice for performance evaluations, for example to compare various quality measures; however, it is not

[1] This problem might be addressed by introducing an absolute minimum threshold on the number of remaining elements after discarding.

optimal when it comes to the level of designing a biometric system. This is mainly due to the difficulty in setting a universal fixed discarding percentage for a system. As shown in our experiments (Figure 4.3), the optimal discarding percentage varies a lot among different databases. For example in the case of independent discarding, the best result (i.e., the lowest EER) is achieved after discarding about 60% of MCC pairs for FVC2004_DB3, versus around 40% for FVC2002_DB2. Another approach in such cases is to discard elements based on a fixed threshold on their absolute quality values. Considering the minutiae quality distributions shown in Figure 4.4, we can estimate the average discarding percentage corresponding to each absolute quality threshold. Figure 4.5 shows such a correspondence for the three databases considered in our experiments. For example, an absolute quality threshold of 66 corresponds on average to around 60% discarding for FVC2004_DB3 and around 50% discarding for FVC2002_DB2, which are both close to the optimal discarding percentages in terms of EER. Therefore, discarding based on an absolute quality threshold might be more reasonable to be considered in a universal system design. On the other hand, such a discarding approach is less dependent to the variability of the number of minutiae in different fingerprints.

Table 4.2 – Summary statistics of the number of extracted minutiae per fingerprint in each database.

Database	Mean	Minimum	Maximum	Std
FVC2002_DB2_A	50.8	9	68	14.0
FVC2002_DB3_A	31.2	6	68	11.5
FVC2004_DB3_A	64.1	19	68	8.7

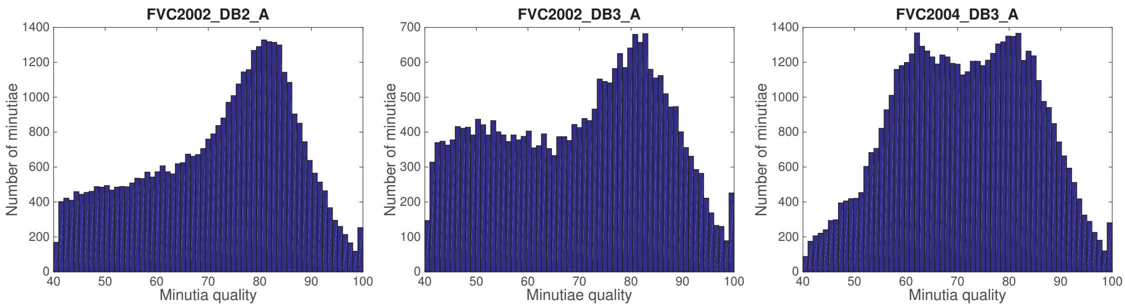


Figure 4.4 – Distribution of minutiae qualities extracted by FingerJetFX.

4.2 Quality based consolidation

In this section, we propose an efficient and rather general approach for incorporating the cylinder quality measures into the MCC-based fingerprint comparison process. The MCC-based

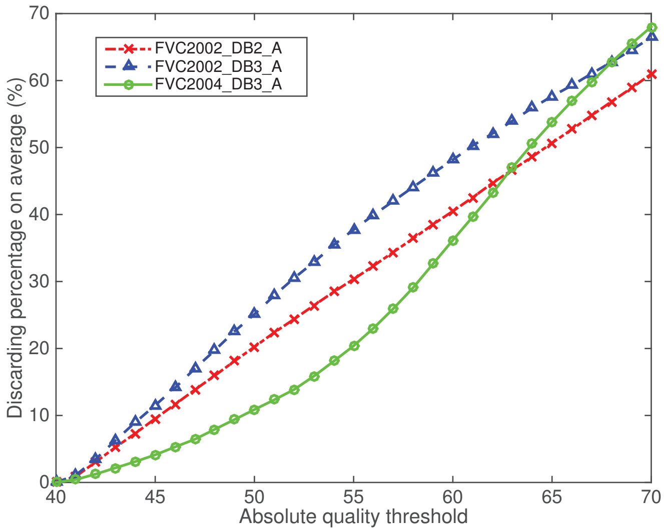


Figure 4.5 – Average discarding percentage corresponding to the absolute quality thresholds in each database.

comparison process starts by computing local similarities for every possible pair of cylinders from the two templates to be compared. Then we need to combine these local similarities into an overall similarity score between two minutiae templates (i.e., two fingerprints). In [18, 21], several methods have been introduced to obtain a global score from the local similarity scores, almost all of them involve a careful selection of candidates from among all possible pairs and then averaging over their local similarities. The cylinder quality measures can be employed to weight the local similarities for candidate selection or final averaging. One approach can be to weight the local similarity between two cylinders based on their pairwise quality. Therefore, if the quality is high for cylinders in a pair, this pair gains more chance to be selected as a candidate and will contribute more to the the global score than a pair of low quality cylinders. However this simple weighting strategy might not be helpful mainly because the incompatible pairs that initially obtained a high similarity by chance might obtain even higher contribution if they are of high quality as well. What we propose here, to reduce the effects of this deficiency, is to utilize the cylinder qualities together with a relaxation approach as in [39, 18].

More precisely, given two templates of MCC descriptors from the two fingerprints to be compared, say $A = \{a_1, a_2, ..., a_{n_A}\}$ and $B = \{b_1, b_2, ..., b_{n_B}\}$, the global matching $Score$ between the two templates is computed through the following steps[2]:

- Firstly, the local similarities between all possible pairs of descriptors respectively from the two templates ($n_A \times n_B$ pairs in total) are computed as in [18].
- Then the n_R pairs having normally the top local similarities are pre-selected, e.g., using a Local Greedy Similarity (LGS) algorithm [21]. Note that n_R is usually greater than the

[2]All MCC related parameters used in the formulations, have been named same as in [18], except otherwise stated.

number of pairs that finally contribute to the global score. Let P be the set of all selected pairs:

$$P = \left\{\left(a_{r_t}, b_{c_t}\right)\right\},\ t = 1, \ldots, n_R, \tag{4.1}$$

$$1 \le r_t \le n_A,\ 1 \le c_t \le n_B,\ n_R = \min\{n_A, n_B\}.$$

- Then through the relaxation phase, the local similarity of each pair is iteratively modified based on its global relationship with the other pairs as follows: Assuming $\lambda_t^{(0)}$ to be the initial similarity of pair t (i.e., $\left(a_{r_t}, b_{c_t}\right)$), the modified local similarity at iteration i of the relaxation procedure is:

$$\lambda_t^{(i)} = \omega_R \cdot \lambda_t^{(i-1)} + \left(\frac{1-\omega_R}{n_R - 1}\right) \cdot \left(\sum_{\substack{k=1 \\ k \neq t}}^{n_R} \rho(t,k) \cdot \lambda_k^{(i-1)}\right), \tag{4.2}$$

where ω_R is a weighting parameter and $\rho(t,k)$ is the measure of compatibility between two pairs: $\left(a_{r_t}, a_{r_k}\right)$ and $\left(b_{c_t}, b_{c_k}\right)$, and can be computed as explained in [18] considering also its distortion-tolerant version in [21]. After executing n_{rel} iterations on all n_R pairs existing in P, the quality-based efficiency of pair t is calculated as:

$$qe_t = \frac{\lambda_t^{(n_{rel})}}{\lambda_t^{(0)}} \cdot Q_t, \tag{4.3}$$

where Q_t is a pairwise quality measure for pair t, and thus depends on both $Q_{a_{r_t}}$ and $Q_{b_{c_t}}$, that are quality measures corresponding to MCC descriptors a_{r_t} and b_{c_t} respectively.

- Finally the n_P pairs with the highest quality-based efficiency qe_t are selected, and the final score is computed using a weighted average with pairwise qualities Q_t as weights:

$$Score = \frac{\sum_{t=1}^{n_P} \left(Q_t \cdot \lambda_t^{(n_{rel})}\right)}{\sum_{t=1}^{n_P} Q_t}. \tag{4.4}$$

With the definition given for quality-based efficiency, we select the final candidate pairs taking into account both factors of compatibility (with other pairs) and quality together, which can address the previously discussed problem of the pairs that obtained randomly an initial high similarity, by penalizing them in the relaxation process.

4.2.1 Evaluations and results

Databases: For this set of evaluations, we considered all fingerprint databases from FVC2002, FVC2004, and FVC2006. There fingerprints are captured by different types of sensors. For example the fingerprints in FVC2004 DB1 are captured using an optical sensor, in FVC2002

DB3 using a capacitive sensor, and in FVC2006 DB3 using a thermal sweeping sensor.

Each database from FVC2002 and FVC2004 contains 800 fingerprint images (including 100 different fingers and 8 samples for each). According to the FVC performance evaluation protocol [24], each sample is compared against the remaining samples of the same finger, to create 2800 genuine pairs in total. The first sample of each finger is also compared to the first sample of the remaining fingers, providing 4950 impostor pairs in total.

Each database in FVC2006 contains 1680 fingerprint images taken from 140 different fingers and there exist 12 samples for each finger. Therefore, there are totally 9240 genuine pairs in each database. However for the impostor pairs, consistent with the FVC performance evaluation protocol [24], we consider only the first sample of each finger, which results in 9730 impostor pairs.

Minutiae extraction: We used two well-known minutiae extractors, the FingerJetFX[3] and the NBIS MINDTCT, to extract minutiae for all fingerprints. Both extractors also provide a quality value for each minutia in the range $[1, 100]$, as explained in Section 3.2. The FingerJetFX keeps by default only those minutiae having quality above 40 up to maximum 68 minutiae for each fingerprint. The NBIS MINDTCT allows up to maximum 100 minutiae per fingerprint image.

MCC parameters: Table 4.1 summarizes all parameters used for MCC template creation and comparison. These parameters are based on the parameters published in [21].

MCC template creation and comparison: The MCC SDK Version 1.4 has been used to create the bit-based MCC descriptors (MCC16b). The Local Greedy Similarity with Distortion Tolerant Relaxation (LGS_DTR) method [21] is used as the baseline for relaxations. To be fairly comparable, we used the same relaxation procedure in our quality-based method.

In other words, the case without quality would be equivalent to consider equal qualities for all minutiae. After normalizing minutiae qualities given by the minutiae extractor, to be in the range $[0, 1]$, a quality value is computed for each cylinder according to Eq. 3.4. The pairwise quality measure, Q_t, for pair t, can be considered as a function of $Q_{a_{r_t}}$ and $Q_{b_{c_t}}$, that are quality measures corresponding to MCC descriptors a_{r_t} and b_{c_t} respectively (i.e., $Q_t = f\left(Q_{a_{r_t}}, Q_{b_{c_t}}\right)$). The two most common functional forms f for pairwise quality are *minimum* and *square root*, as expressed in Eqs 4.5 and 4.6 respectively:

$$Q_t = min\left(Q_{a_{r_t}}, Q_{b_{c_t}}\right), \quad \texttt{or} \tag{4.5}$$

$$Q_t = \sqrt{Q_{a_{r_t}} \times Q_{b_{c_t}}}. \tag{4.6}$$

[3]The FingerJetFX software by default does not provide any minutiae template for very small-sized fingerprints. However, we removed this condition from the code, making it possible to extract the templates containing very few minutiae.

However the *minimum* function is generally preferred due to the fact that it penalizes more the pairs which include a low-quality and a high-quality descriptor. The corresponding Equal Error Rates (EERs) for 8 real fingerprint databases from FVC2006, FVC2004, and FVC2002 are reported in Table 4.3 separately for each minutiae extractor. DET curves (false non match rate vs. false match rate) are also shown for 4 selected databases from FVC2006 and FVC2004 in Figures 4.6 and 4.7 for NBIS MINDTCT and FingerJetFX minutiae extractors, respectively.

Table 4.3 – Equal Error Rate (EER) evaluated on all real fingerprint databases from FVC2006, FVC2004, and FVC2002 using baseline and quality-based MCC methods. The quality-based method is denoted by MCC+Q_minim where the minimum function is used to compute the pairwise quality, and by MCC+Q_sqrt where the square root function is used to compute the pairwise quality. The bold values highlight the least EER in each row.

(a) Minutiae and quality extracted by NBIS (MINDTCT)

	EER (%)		
Database	MCC	MCC+Q_mini	MCC+Q_sqrt
FVC2006_Db2_a	0.62	**0.56**	0.62
FVC2006_Db3_a	5.45	3.98	**3.96**
FVC2004_Db1_a	7.17	7.18	**7.05**
FVC2004_Db2_a	7.91	7.58	**7.56**
FVC2004_Db3_a	4.27	**3.83**	3.91
FVC2002_Db1_a	1.36	**1.20**	1.21
FVC2002_Db2_a	0.61	0.63	**0.59**
FVC2002_Db3_a	7.28	**6.34**	6.49

(b) Minutiae and quality extracted by FingeJetFX

	EER (%)		
Database	MCC	MCC+Q_mini	MCC+Q_sqrt
FVC2006_Db2_a	0.48	**0.44**	**0.44**
FVC2006_Db3_a	4.32	**3.92**	4.10
FVC2004_Db1_a	4.75	**4.68**	4.72
FVC2004_Db2_a	8.16	**7.81**	8.10
FVC2004_Db3_a	3.89	**3.23**	3.41
FVC2002_Db1_a	**0.891**	0.975	0.967
FVC2002_Db2_a	0.59	**0.57**	0.61
FVC2002_Db3_a	4.71	**4.57**	4.78

4.2.2 Discussion

Out of 8 databases of real fingerprints considered for evaluations, the comparison performance based on the EER is improved by using the quality-based consolidation method for all databases in the case of NBIS MINDTCT minutiae and for 7 databases in the case of FingerJetFX using either $minimum$ or $squareroot$ pairwise function. However, the $minimum$ function generally outperforms the $squareroot$, especially for the FingerJetFX minutiae. The level of performance improvement also varies among different databases from just a minor improvement for cases like FVC2004_DB2 to a significant improvement for cases such as FVC2006_DB3, where the EER goes down to 3.96% from 5.45% after embedding the MINDTCT minutiae quality in the MCC based comparisons. Even in cases like FVC2006_DB2 where the EER is already very low using the baseline MCC, we still observe some degrees of improvement (though not significant) after embedding the minutiae quality via the proposed consolidation method.

The FVC2002_DB3 and FVC2004_DB3 contain several small-sized samples, in which the minutiae templates contain only a few minutiae. That is also a reason why the performance on these databases relatively degrades, but quality-based method improves the performance even in such cases. Note that all the MCC based methods depend on the minutiae extraction performance as well, for example FingerJetFX minutiae usually outperform the MINDTCT ones on average.

The same set of experiments have also been carried out on the three synthetic databases existing beside the real databases presented above. The resulting EERs are presented in Table table:EER-FVC-Synthetic, where an interesting fact is observed that the quality-based method failed in all 3 cases using the MINDTCT minutiae and quality. This might be because the MINDTCT quality assessment does not perform equally well for synthetic fingerprints.

Table 4.4 – Equal Error Rate (EER) evaluated on synthetic fingerprint databases from FVC2006, FVC2004, and FVC2002 using baseline and quality-based MCC methods.

(a) Minutiae and quality extracted by NBIS (MINDTCT)

	EER (%)		
Database	MCC	MCC+Q_mini	MCC+Q_sqrt
FVC2006_Db4_a	**5.81**	6.44	6.49
FVC2004_Db4_a	**3.83**	4.15	4.10
FVC2002_Db4_a	**3.08**	3.17	3.26

(b) Minutiae and quality extracted by FingeJetFX

	EER (%)		
Database	MCC	MCC+Q_mini	MCC+Q_sqrt
FVC2006_Db4_a	10.80	**10.75**	10.80
FVC2004_Db4_a	3.98	**3.78**	3.85
FVC2002_Db4_a	3.47	3.50	**3.44**

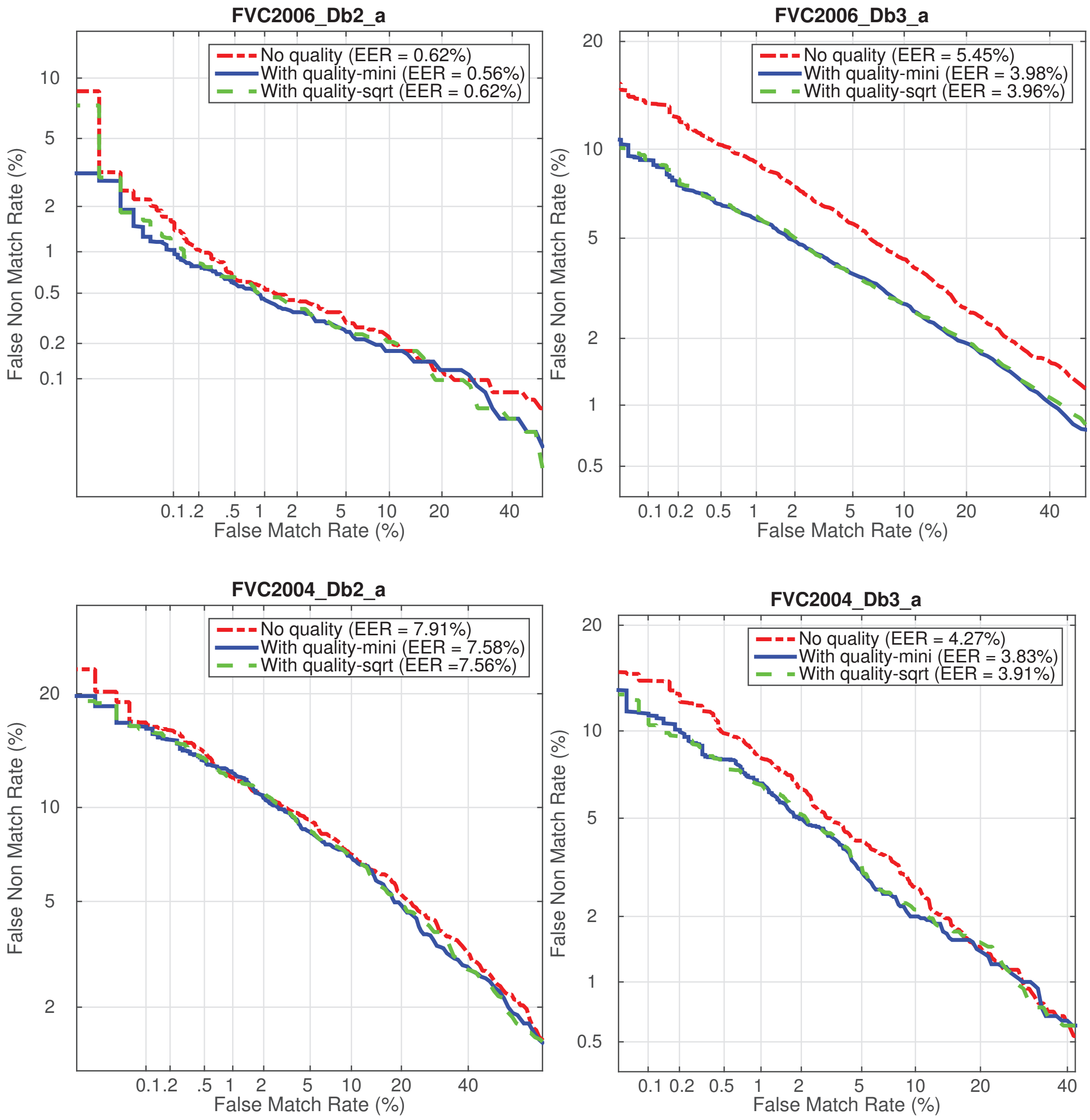


Figure 4.6 – DET curves showing an increase in the matching performance by embedding minutiae quality in MCC based comparisons using minutiae extracted by NBIS MINDTCT.

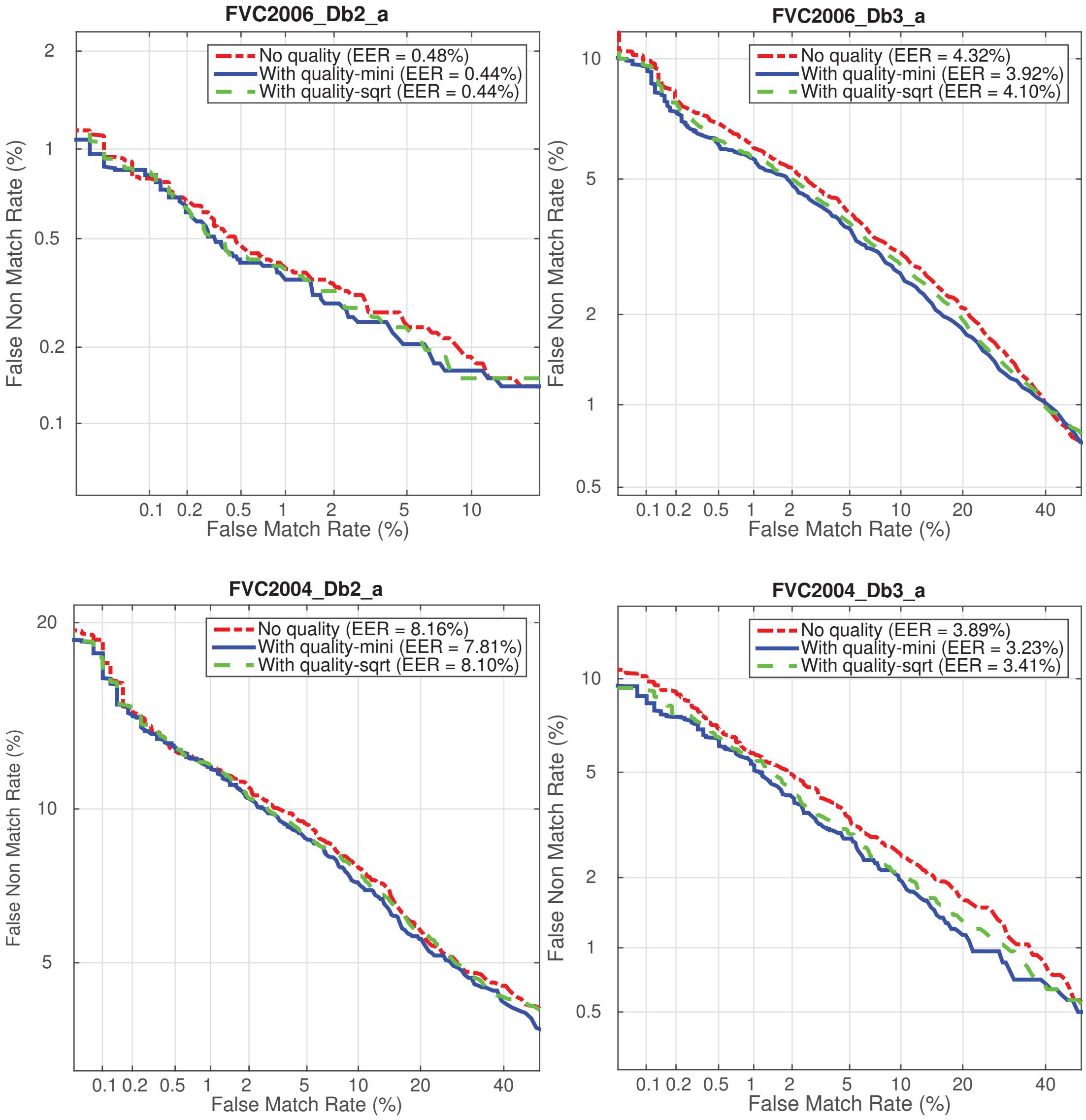


Figure 4.7 – DET curves showing an increase in the matching performance by embedding minutiae quality in MCC based comparisons using minutiae extracted by FingerJetFX.

5 Supervised embedding of local quality measures using synthetic fingerprints

In this chapter, we propose a supervised approach based on a binary classification model which can be trained to modify the local similarity scores based on one or several local quality features. Unlike the methods proposed in Chapter 4, this method requires some reliable training data to provide the desired results. The training data must be labeled in order to differentiate between genuine and impostor minutiae pairs. On the other hand, it must be a good representative of the real-domain data at least in terms of the local quality measures considered for embedding. Two possible candidates for training data are synthetic fingerprints or manually labeled data. In this chapter, synthetic fingerprints are used to build a training set for our model. This chapter is actually an updated version of our preliminary work published in [60].

5.1 Synthetic fingerprints and ground truth minutiae

Synthetic fingerprint images are currently being used for testing, developing, and optimizing fingerprint recognition systems [84]. They are found to be helpful, mainly due to:

1. availability of labeled ground truth minutiae information,
2. possibility to add different levels of noise and deformation,
3. possibility to create a large number of samples in a short time.

Synthetic fingerprints generated by Synthetic Fingerprint Generator (SFinGe) [15, 14] allowed us to create a large set of genuine and impostor minutiae pairs, thus made it possible to form a set of genuine/impostor MCC pairs for our evaluations. This set is then used as training data to learn a binary classification model based on logistic regression. The model combines local similarity scores and cylinder quality measures into new modified similarity scores. In this model, the modified similarity score for a given MCC pair is estimated as log-odds of the pair being genuine.

5.2 Evaluating cylinder quality from synthetic data

Another possible advantage of having access to the ground truth minutia could be to evaluate the discriminability of the local minutiae descriptors within the synthetic set. For example, there are some cylinders that tend to produce high (or low) similarity scores with all the other cylinders no matter they are matched or not. The set of ground truth minutiae/cylinders allows to form a set of match and non-match cylinders for a given cylinder. This set can be used then to derive a measure of discriminability by comparing the local similarity scores within the two classes (genuine/impostor) for each cylinder.

5.3 Local similarity scores vs. local quality measures

An automatic minutia extractor usually detects many artifacts as minutiae in a low-quality fingerprint image. A reliability criterion is then used to reject many of those false minutiae [84]. However, some of them still remain in the final list of extracted minutiae for a fingerprint, especially if there exist some low-quality regions, for example those having scratches or unclear ridges. If the minutiae are labeled in each fingerprint so that we can determine rather accurately whether a pair of minutiae from two fingerprints is a genuine match, then we can form a set of genuine and impostor cylinder pairs as well. A pair of cylinders (MCC descriptors) from two fingerprints is assumed to be genuine, if their corresponding central minutiae are genuinely matched. This set of genuine/impostor MCC pairs can be helpful for analysis and training purposes.

The local similarity scores versus the pairwise cylinder quality measures[1] are shown in Figure 5.1 for a large set of genuine and impostor MCC pairs. An interesting observation here is that pairwise cylinder quality measures seem to be more positively correlated with local similarity scores for the genuine pairs, compared to the impostor pairs. For example, the Pearson's correlation coefficient (ρ) between the two factors is 0.288 for the genuine pairs versus -0.031 for the impostor pairs in Figure 5.1.

5.4 Classification model for embedding local quality measures

5.4.1 Modified similarity scores using logistic regression

In this section, we propose a method to take the advantage of local quality measures to modify the local similarity scores with the final aim of improving global matching performance. The method is based on a binary (2-class) classification model trained by a set of genuine/impostor MCC pairs extracted from the synthetic fingerprints. For a given MCC pair, the local similarity score and the pairwise cylinder quality measure are the inputs, and the modified similarity score is the output, defined as the log-odds (logit) of being genuine. In other words, we use

[1] Here we used the central minutia quality (obtained from the FingerJetFX) as cylinder quality measure. The pairwise cylinder quality is considered here the minimum cylinder quality of the two MCC descriptors in a pair.

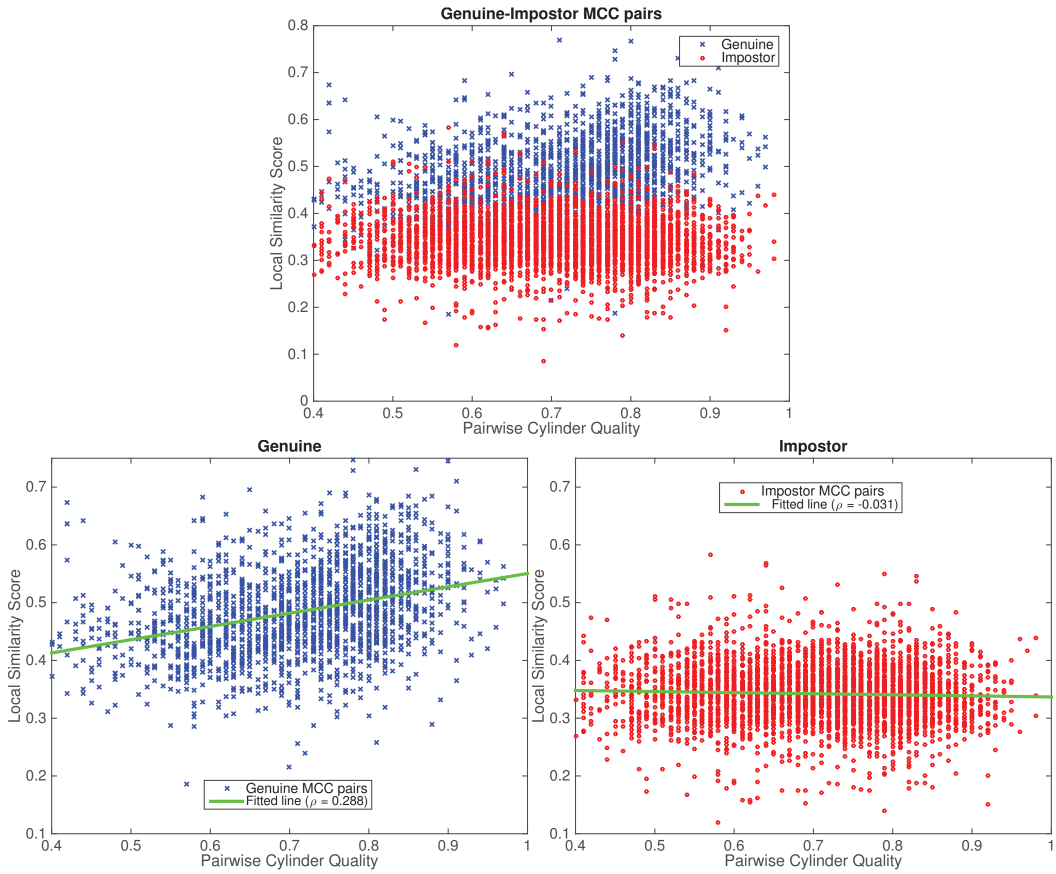


Figure 5.1 – Local similarity scores versus pairwise cylinder quality measures for genuine (blue cross) and impostor (red circle) MCC pairs (combined above and separated below). The Pearson's correlation coefficient (ρ) between the two factors is also calculated for genuine and impostor pairs separately, and shown in each figure together with the corresponding fitted line.

the synthetic fingerprint data to train a logit function in order to combine the local quality measures with the local similarity score into a modified similarity score. The new similarity score can be used later to improve the pre-selection of MCC pairs as well as the global matching performance. Here the local similarity of each pair is proposed to be modified via a linear function trained using logistic regression based on the following model:

Given two MCC templates $A = \{a_1, a_2, ..., a_{n_A}\}$ and $B = \{b_1, b_2, ..., b_{n_B}\}$, let $\Gamma^{(old)}_{(r,c)}$ be the initial local similarity of the MCC pair (a_r, b_c), i.e., $\Gamma^{(old)}_{(r,c)} = \Gamma(a_r, b_c), 1 \le r \le n_A, 1 \le c \le n_B$. Considering $[\beta_0, \beta_1, \beta_2, \beta_3]$ as coefficients of the linear function f, the modified similarity score $\Gamma^{(new)}_{(r,c)}$ for the pair (a_r, b_c) can be estimated in the form of a logit as follows:

$$\Gamma^{(new)}_{(r,c)} = \ln\left(\frac{p_{(r,c)}}{1 - p_{(r,c)}}\right) = f(\Gamma^{(old)}_{(r,c)}, Q_{(r,c)})$$

$$= \beta_0 + \beta_1 \Gamma^{(old)}_{(r,c)} + \beta_2 Q_{(r,c)} + \beta_3 Q_{(r,c)} \times \Gamma^{(old)}_{(r,c)}, \tag{5.1}$$

where $p_{(r,c)}$ is the (estimated) probability of the MCC pair (a_r, b_c) being genuine given the inputs mentioned above. $Q_{(r,c)}$ denotes the pairwise quality measure of this pair, thus depending on both Q_{a_r} and Q_{b_c}, which are cylinder quality measures corresponding to the MCC descriptors a_r and b_c respectively. It is worth noting that here we added an interaction term $(Q_{(r,c)} \times \Gamma^{(old)}_{(r,c)})$, which might not be necessary in general. Other quality measures can be simply added to this model as new terms with new coefficients.

5.4.2 Global matching

The set of final pairs $P = \{(\hat{r}_j, \hat{c}_j)\}$, $j = 1, ..., n_P$ is chosen based on a greedy approach like LGS as given in Algorithm 2, then the global matching $Score$ can be computed by averaging as follows:

$$Score = \frac{\sum_{j=1}^{n_P} \Gamma^{(new)}_{(\hat{r}_j, \hat{c}_j)}}{n_P}, \tag{5.2}$$

where n_P is chosen according to Eq. (2.5).

Algorithm 2 Pre-selection using modified Local Greedy Similarity (LGS)

0: $P = \phi$
1: While $|P| < n_P$
2: $(\hat{r}, \hat{c}) = \arg\max_{(r,c)} \left\{ \Gamma^{(new)}_{(r,c)} \mid \nexists (r', c') \in P \quad \text{with} \quad r' = r \vee c' = c \right\}$
3: $P = P \cup \{(\hat{r}, \hat{c})\}$
4: End While

5.5 Experiments and results

5.5.1 Synthetic fingerprint data

The SFinGe is known for generating large databases of rather realistic fingerprint images [22], which are being used for testing, developing, and optimizing fingerprint recognition systems. Using SFinGe, we have generated a large database of synthetic fingerprints containing 400 samples (100 fingers×4 samples/finger), together with the labeled ground truth minutiae data. By "labeled" we mean that each ground truth minutia has a unique label (index) in different samples of the same finger. Therefore, the correspondence between the ground truth minutiae within different samples is known in the database.

In the last step of synthetic fingerprint generation, some specific noise [23] and deformation have been added in different levels to produce varying quality fingerprints. The average noise level is intentionally chosen to be "medium/high" for this database to make it challenging for minutiae extractors and comparison (matching) method.

5.5.2 Genuine/impostor MCC pairs and training

Since the Ground Truth (GT) minutiae are labeled for the synthetic fingerprints, we can determine rather accurately if an extracted minutia is true or false. This can be done by searching a neighboring area around the position of each GT minutia and also by setting a threshold on angular difference between the extracted and GT minutiae. Having true minutiae linked to the GT minutiae labels, we can create a large set of genuine and impostor minutiae pairs within the set of extracted minutiae.

For our experiments, we have used the FingerJetFX [2] for extracting the minutiae and their quality from synthetic and real fingerprint images. The cylinder quality measure for each MCC descriptor is estimated by the quality of its central minutia extracted by the FingerJetFX. Pairwise quality $Q_{(r,c)}$ of the MCC pair (a_r, b_c) is calculated using a minimum function as follows: $Q_{(r,c)} = \min\left(Q_{a_r}, Q_{b_c}\right)$, where Q_{a_r} and Q_{b_c} represent the cylinder quality measures of the descriptors a_r and b_c respectively.

We have used the binary MCC descriptors (MCC16b) [18] for our experiments. The MCC descriptors, the local similarity scores and the number of final pairs n_P are obtained using the MCC parameters given in Table 4.1. The MCC SDK Version 1.4 has been also used for MCC template creation and matching.

By setting the search thresholds at 12 pixels for distance and 15 degrees for angular difference, we formed a large set of genuine/impostor minutiae pairs. The MCC pairs are considered to be genuine if their central minutiae are genuine, and impostor otherwise. Therefore, a set of genuine/impostor MCC pairs could be created. This set of feature-level genuine/impostor pairs can be very useful for testing and optimizing of the methods integrating MCC and local quality measures.

Using a large subset of the generated synthetic database (500×4 samples), 28518 genuine MCC pairs have been formed. There are obviously many more impostor pairs, but we have chosen 54621 impostor MCC pairs (double the size of genuine pairs) for our experiments. This set of genuine/impostor MCC pairs is used as training data for maximum likelihood (ML) estimation of the coefficients $[\beta_0, \beta_1, \beta_2, \beta_3]$ in the multinomial logistic regression model given in Eq. (5.1). The trained coefficients and their corresponding p-values are reported in Table 5.1. Once the coefficients have been learned, the function is ready to modify the similarity scores using local quality measures, such as the pairwise cylinder quality measures considered in our experiments.

Table 5.1 – Values of the coefficients trained using logistig regression

Variable	Range	Coefficient	p-value
constant	–	$\beta_0 = -3.824$	0.0023
old local similarity score ($\Gamma^{(old)}_{(r,c)}$)	[0, 1]	$\beta_1 = 6.463$	0.0000
pairwise cylinder quality ($Q_{(r,c)}$)	[0.4, 1]	$\beta_2 = -20.545$	0.0049
interaction term ($Q_{(r,c)} \times \Gamma^{(old)}_{(r,c)}$)	[0, 1]	$\beta_3 = 46.044$	0.0000

5.5.3 Global matching performance

To compare the global matching performance of the proposed method, we have evaluated it on both synthetic and real fingerprint data. A separate subset of the generated synthetic database containing 400 fingerprints (100×4) is selected as the first synthetic data for testing. The FVC2004_DB4_A database is also chosen as another synthetic database. The FVC2002_DB2_A and FVC2004_DB3_A databases are chosen as real databases, each containing 800 fingerprints (100×8). We formed the genuine and impostor fingerprints according to the FVC performance evaluation protocol [84], in order to generate the DET curves. The resulting DET curves are shown for synthetic and real data in Figures 5.2 and 5.3, respectively. In these figures, the DET curve of the classical LGS method is compared against that of the LGS method modified using the pairwise cylinder quality measures. As shown in Figures 5.2 and 5.3, the modified similarity scores outperform the classical ones in both synthetic and real databases. However, the improvement is clearly higher for the synthetic databases, possibly due to the fact the modifying model is trained using the synthetic data. For example, if we compare these results with the results obtained using the discarding method in Section 4.1.3 for the FVC2002_DB2_A and FVC2004_DB3_A databases, we see that discarding with a proper percentage can bring better results in both cases.

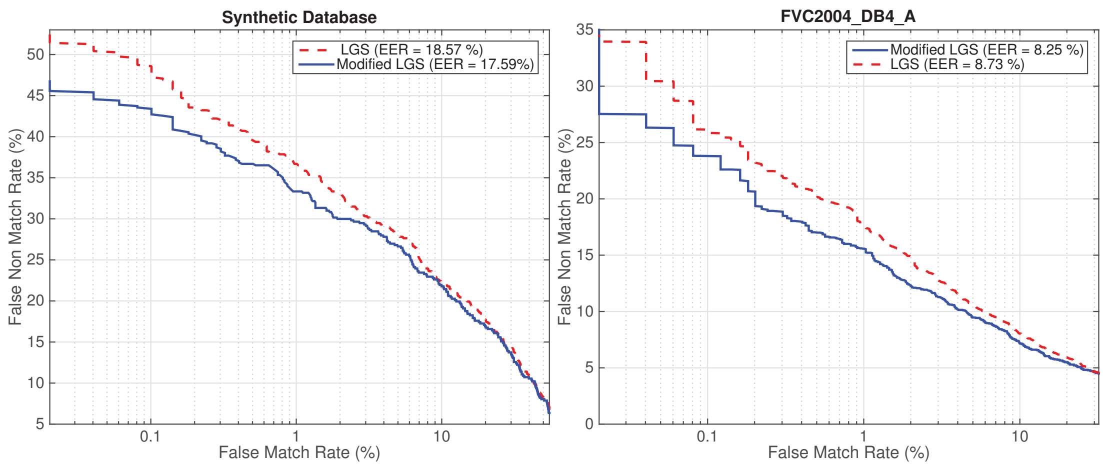


Figure 5.2 – DET curves comparing the global matching performance of classical LGS with modified LGS on synthetic fingerprints.

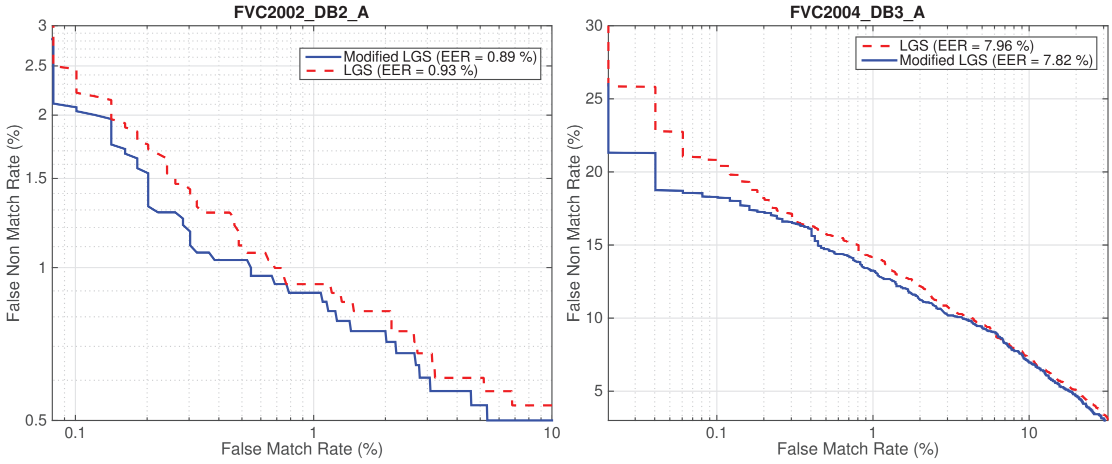


Figure 5.3 – DET curves comparing the matching performance of classical LGS with modified LGS on FVC2002_DB2_A and FVC2004_DB3_A databases of real fingerprints.

6 Comparative evaluation of cylinder quality measures

In this chapter, we present a set of supplementary experiments to evaluate cylinder quality measures based on different local quality assessment methods for MCC based fingerprint comparisons. We also investigate the effect of central weighting parameter and quality block size in the cylinder quality measures.

6.1 Evaluation of candidate local quality features

In order to evaluate different local quality assessment methods for estimating cylinder quality measures, we considered the discarding approach proposed in Section 4.1 as a baseline algorithm. This approach relies on discarding low quality elements from the local similarity matrix before global comparison. The low quality elements are determined based on independent or pairwise cylinder quality measures.

In a simplified setting for our experiments, we used only the central cylinder area for estimating cylinder quality measures, consistent with the major role that this area plays in the quality of MCC descriptors as explained in Section 3.6. Otherwise, we have used exactly the same setting and parameters as given in Section 4.1.1 throughout this chapter. In this set of experiments, we considered only the FVC2004_DB3_A database since it has on average a relatively high number of minutiae per fingerprint, making it more suitable for evaluations using the discarding approach. We have also taken into account the usual 32x32 quality blocks containing the central minutiae. Moreover, The minimum function has been used for calculating the pairwise cylinder quality measures. Table 6.1 summarizes all local quality measures considered for evaluations in this chapter. For a more detailed description of each measure, one can refer to Sections 3.5 and 3.2. However in our experiments, we considered only the minutiae quality obtained from the FingerJetFX. This is mainly due to the fact that minutiae and quality extracted by the FingerJetFX usually outperformed those from the NBIS MINDTCT in our previous experiments. In Figure 6.1, the Equal Error Rate (EER) has been depicted versus the discarding percentage based on pairwise cylinder quality measures obtained from different local quality features, namely LCS, OCL, FDA, GAB and FJFX, as mentioned in Table

Abbreviation	Full name
OCL	Orientation Certainty Level
LCS	Local Clarity Score
FDA	Frequency Domain Analysis
OF	Orientation Flow
RVU	Ridge Valley Uniformity
GAB	Gabor filter-based quality [90]
FJFX	FingerJetFX minutia quality

Table 6.1 – Local quality measures considered for comparative evaluations

6.1. The RVU and OF are excluded from this graph because they have shown not compatible behavior comparing to the other measures, as shown in Figure 6.2. As seen in these graphs, no quality measure outperforms the others in the whole range. But for small to medium discarding percentages, the cylinder quality measures based on the LCS seem to provide the best performance, while the FJFX and GAB usually outperform the others for higher percentages. The minimum EER is achieved using the GAB (nearly followed by the FJFX) at around 60% discarding.

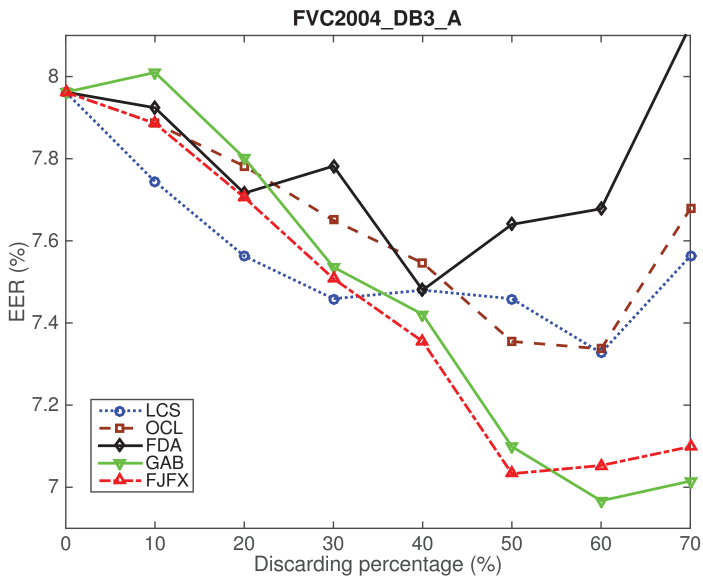


Figure 6.1 – EER versus discarding percentage based on pairwise cylinder quality measures obtained from different local quality features (LCS, OCL, FDA, GAB and FJFX). The local quality is computed on 32 × 32 blocks containing central minutiae except for GAB and FJFX.)

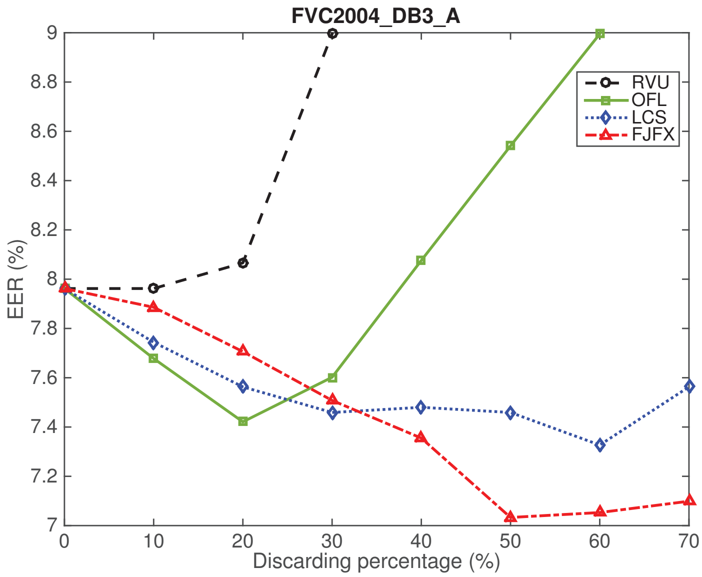


Figure 6.2 – EER versus discarding percentage based on pairwise cylinder quality measures obtained from different local quality features (RVU, OF, LCS and FJFX). The local quality is computed on the blocks of 32 × 32 pixels for RVU, OF and LCS.

6.2 Quality blocks centered at the minutiae positions

In the next set of experiments, we modify the position of quality blocks to be centered at the position of central minutia within each cylinder, as explained in Section 3.4. The results presented in Figure 6.4 for the FVC2004_DB3_A database show that re-positioning the 32 × 32 quality blocks to be centered at the central minutia position improves the performance for the three local quality features considered: LCS, OCL, and FDA. More comprehensive results for the same database are presented in Figure 6.3, where performance of the main local quality features have been compared based on the same discarding approach but using the centered blocks of 32 × 32 pixels for LCS, OCL and FDA. For this database, the cylinder quality measures obtained from the LCS seem to provide the best performance for small to medium discarding percentages (up to around 35%), however the minimum EER is still achieved using the GAB, followed nearly by the FJFX at around 60% discarding. The quality measures such as the LCS in this case, which provide the lower EERs at lower discarding percentages, might be preferred for certain applications such as filtering out the very worst cylinders from each template.

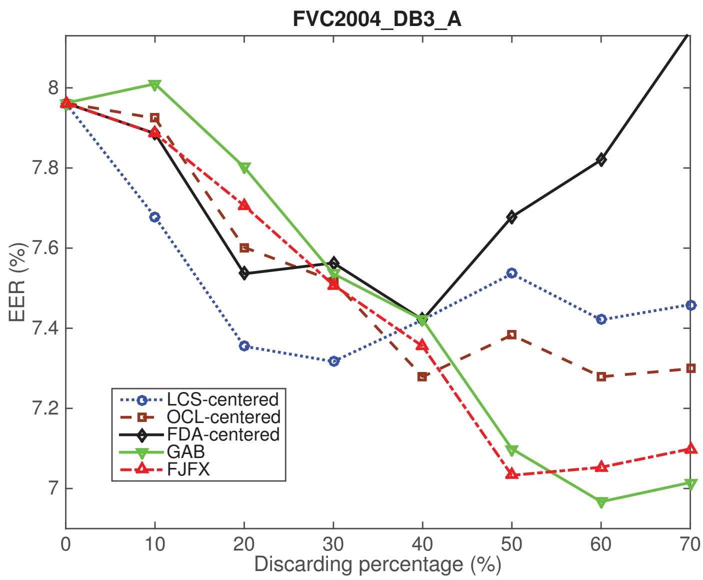


Figure 6.3 – EER versus discarding percentage for FVC2004_DB3_A. The local quality measures LCS, OCL and FDA are computed here on 32 × 32-pixel blocks centered at the position of central minutia.

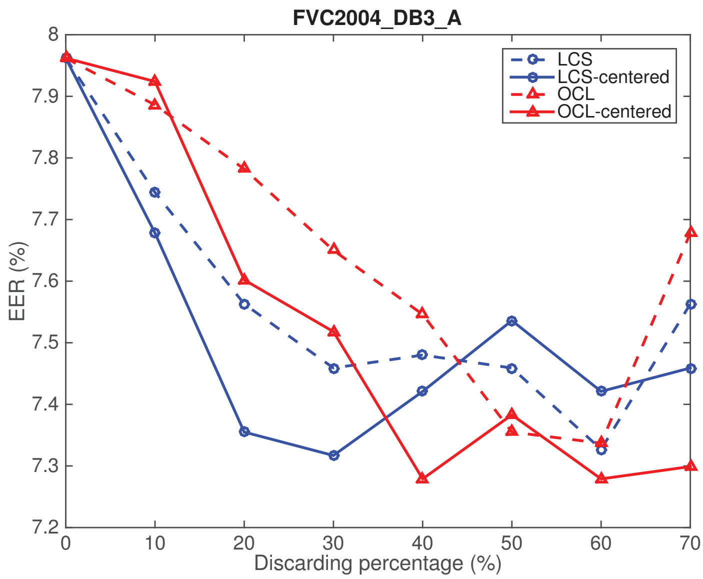


Figure 6.4 – EER versus discarding percentage based on pairwise cylinder quality measures obtained from centered and non-centered quality blocks of 32 × 32 pixels.

6.3 Quality block size

The size of quality blocks is definitely an important factor in evaluation of cylinder quality measures. By quality blocks we mean the blocks of the image, on which the local quality are estimated. For most of the existing local quality assessment methods we need to have at least two ridges and valleys in the block to be able to estimate the quality, so the minimum block size is usually considered to be 16 × 16 pixels on 500 ppi fingerprint images. In this Section, we performed several experiments to compare the effect of quality block size in our problem. To do so, we considered the central blocks of sizes 16 × 16, 24 × 24, 32 × 32 and 64 × 64 pixels for estimating cylinder quality measures. The evaluations have been done again by applying the discarding approach using pairwise cylinder quality measures obtained from the centered quality blocks. The evaluation results using the OCL quality measures have been presented in Figure 6.5 for different block sizes ranges from 16 × 16 to 64 × 64 pixels. For most of the discarding percentages considered, the block sizes of either 24 × 24 or 32 × 32 pixels provide better performance than the other sizes.

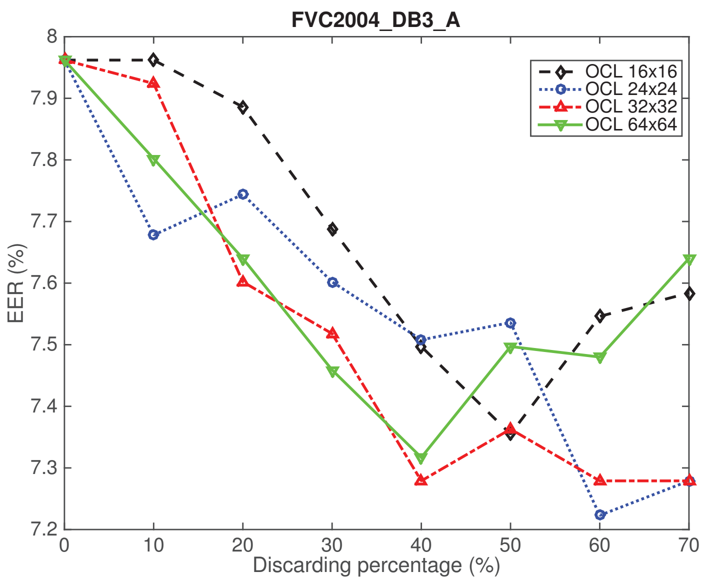


Figure 6.5 – EER versus discarding percentage based on pairwise cylinder quality measures obtained from the OCL quality measures with different quality block sizes.

6.4 Effect of centralized weighting in cylinder quality assessment

In this section, we refer to the estimation of cylinder quality measures proposed in Eq. 3.4 via a centralized weighting scheme. In this set of experiments we investigate the effect of the parameter σ_q, which determines the rate of decay for the weights proposed in Eq. 3.4. To do so, we consider several FVC databases including FVC2006_DB2, FVC2006_DB3 and FVC2004_DB3. We use the quality-based consolidation method (refer to Section 4.2) in order to embed the cylinder quality measures given a wide range of σ_q to observe its effect on the final comparison performance. Figure 6.6 shows the EER versus the parameter σ_q based on the minutiae and quality extracted by NBIS MINDTCT and FingerJetFX. The minimum EER is achieved at as low as $\sigma_q = 5$ for FVC2004_DB3_A with the FingerJetFX minutiae and as high as $\sigma_q = 25$ for FVC2004_DB3_A with NBIS MINDTCT minutiae.

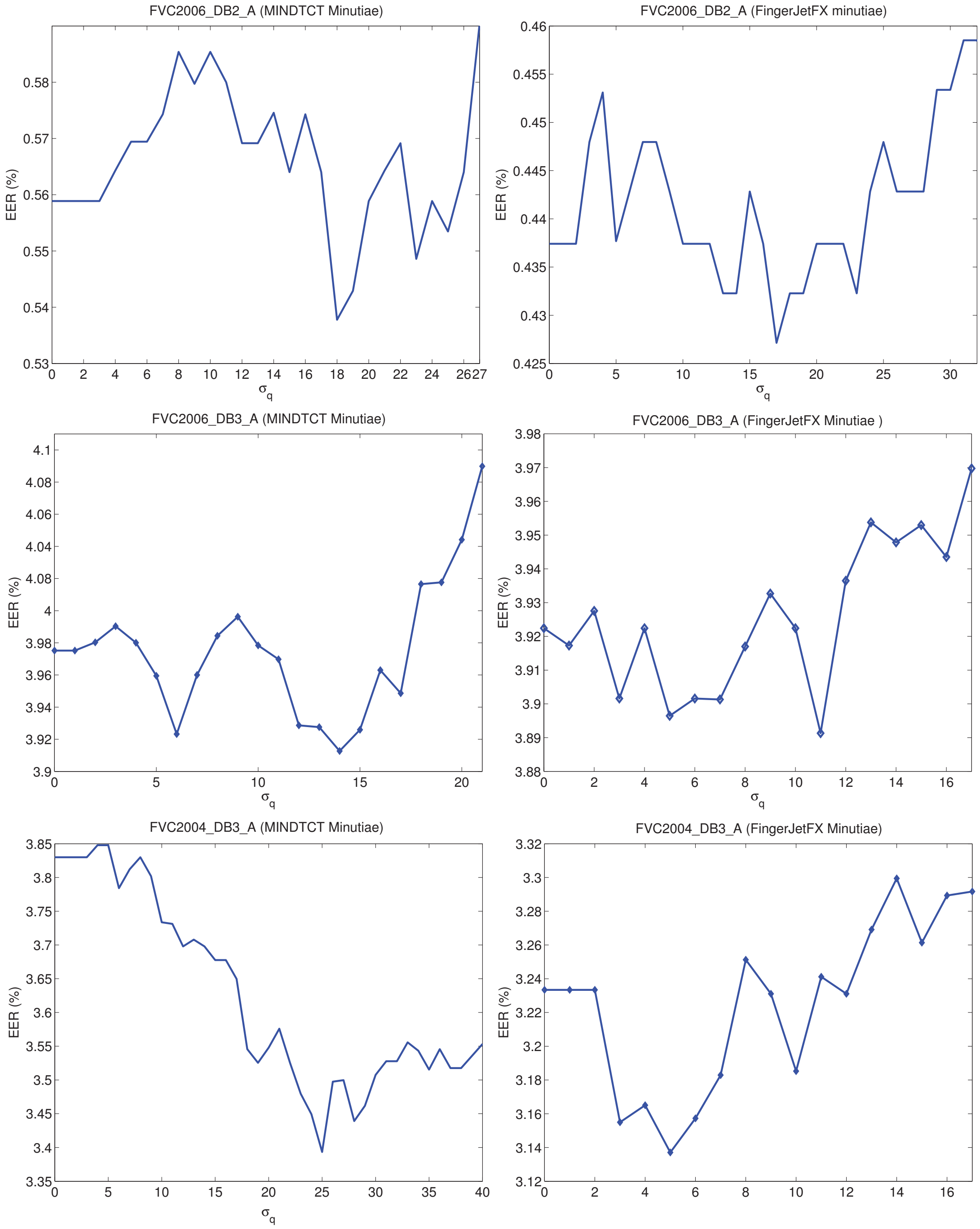


Figure 6.6 – EER versus σ_q for FVC2006_DB2_A, FVC2006_DB3_A, and FVC2004_DB3_A based on the minutiae and quality extracted by NBIS MINDTCT (left) and FingerJetFX (right).

7 Latent print comparison via embedding local quality measures

7.1 Minutiae-based latent fingerprint comparison

Although there are rather accurate methods for automatic minutiae extraction from plain or rolled fingerprints, extracting minutiae from latent fingerprints is not yet a task to be reliably done in a fully automatic way. Having only a small area, low quality and large background noise and non-linear distortion are the main problems which make it difficult to automatically extract reliable minutiae from latent fingerprints. That is why the minutiae in latent fingerprints are usually marked by trained examiners, which eventually introduces an interoperability problem between this kind of minutiae and those extracted automatically, for example in the matched rolled fingerprints [93]. Apart from minutiae extraction part, the matching itself is also much more difficult for latent fingerprints due to the same problems. For instance, in a usual forensics scenario, a distorted latent fingerprint with a few minutiae (small area) needs to be matched with a fully rolled fingerprint having normally much more minutiae. In such a case, even if we could have perfectly detected minutiae, it would not have been easy to match this two minutiae templates. The situation would be even worse if we use global minutiae matching which is not usually robust against nonlinear distortions and needs accurate alignments. That is mainly why most of the minutia-based efforts for latent fingerprint matching are based on the local matching techniques. In sum, latent fingerprint matching using minutiae is considered a challenging problem, and is obviously far from the normal case of plain to plain matching in terms of performance. Recently there have been several works done to improve the matching performance, for example by using extended features [63], fusion of manually marked and derived minutiae [93], or using descriptor-based Hough transform [92], yet most of these methods rely on a baseline local minutiae matching which is the main issue to be addressed in this thesis, especially in presence of MCC descriptors.

Table 7.1 – Distribution of subjective minutiae quality within the latent set of NIST SD27

Subjective minutiae quality	All	Good	Bad	Ugly
Good	3416	2015	888	513
Medium	1298	483	450	365
Poor	488	206	157	125
Undetermined	80	64	0	16

7.2 Local quality in latent fingerprints

The poor quality is one of the most important factors that reduces the comparison performance for latent fingerprints. Therefore, local quality assessment of latent fingerprint images is of great importance to ensure high recognition accuracy. Many local and global quality measures have been already proposed for plain and rolled fingerprints such as those presented in Chapter 3. However, most of them fail to provide the same results for latent fingerprints. Ridge Clarity Map [115, 114] is among a few (if not the only one) local quality measures developed specifically for the latent fingerprints.

7.2.1 Minutiae quality assessment by examiners

Since the latent fingerprint minutiae are often marked manually by some trained experts, the minutiae quality are not usually computed automatically. For example, in the NIST Special Database 27 (SD27) [89] of latent fingerprints, the examiners are asked to subjectively rate the quality of each marked minutia in three possible levels: Good, Medium and Poor. The quality has been rated based on the local conditions of the image around each detected minutia, and also based on how clearly the type of minutia can be identified. The distribution of different quality levels within the ideal latent set of NIST SD27 database is given in Table 7.1 which shows the majority of minutiae are rated as Good quality. The main problem of such subjective qualities is that the expert examiners are not so reliable when it comes to assigning a quality value to the minutiae already filtered and marked by them. These qualities are also quantized, so they might be rather inconsistent among different cases and thus not sufficiently informative.

7.3 Embedding subjective quality in MCC based latent fingerprint comparison

The NIST SD27 database available at [89] is considered for evaluations in this chapter. It consists of 258 latent fingerprint cases and their corresponding rolled tenprints. This is one of the most challenging database containing latent fingerprints together with mated rolled tenprints. Based on the overall quality of latent fingerprint images, the 258 latent fingerprints in the NIST SD27 database are divided into three general categories: "Good" (88 cases), "Bad"

Table 7.2 – Normalized numerical values for subjective minutiae quality

Minutia quality	Value in template	Value assigned
Good	6	1
Medium	11	0.9123
Poor	16	0.8246

(85 cases), and "Ugly" (85 cases). The minutiae information (location and ridge direction at each minutia point) is provided for all fingerprints in the database. The tenprints minutiae are extracted by an automatic AFIS system, and then validated by examiners. For latent fingerprints, minutiae are manually extracted by professional latent examiners. A subjective minutia quality is provided for each latent fingerprint minutia, but not for the tenprints. This subjective quality is described on three levels by the examiners: Good, Medium or Poor. The distribution of subjective minutia quality within the ideal latent set of the NIST SD27 is given in Table 7.1.

By embedding the objective local quality measures based on the Ridge Clarity Maps [115] introduced in Section 3.5.8, we did not achieve any meaningful improvement in the identification performance using MCC-based comparison on this database. None of the local quality features proposed for fingerprints and palmprints in Chapter 3 could also produce some meaningful quality maps for the latent prints in this database. Therefore, we consider the subjective minutiae quality for our experiments in this section. In order to use the subjective minutiae quality information, we first normalized the given numerical values using a min-max normalization given in Eq. 7.1 based on the fact that the minimum possible quality value in the NIST templates[1] is considered to be 63.

$$Q_{assigned} = \frac{63 - Q_{old}}{57}. \tag{7.1}$$

The new normalized quality value assigned to each subjective quality level is given in Table 7.2. For each cylinder, the cylinder quality measure is estimated to be the subjective quality of its central minutia normalized according to Table 7.2. It is used then to obtain the pairwise quality Q_t needed for the quality-based consolidation method (refer to Eqs 4.3 and 4.4). Since minutiae quality are only available for the latent fingerprints, the pairwise quality Q_t is chosen to be the cylinder quality of the latent case for each pair t. For comparative evaluations, we used the same relaxation procedure (Eq. 4.2) in all our experiments, meaning the case without quality is equivalent to the case where equal quality is considered for all the minutiae. The parameters for MCC template creation and comparison have been chosen according to the values given in Table 7.3, which are the last set of parameters released in the MCC SDK Version 1.4 [3], except the parameter δ_θ which is set to be $\frac{\pi}{4}$. This is based on the fact that this parameter controls the maximum rotation allowed between two fingerprints, and is usually restricted at $\frac{\pi}{4}$ for experiments on the NIST SD27. The MCC SDK Version 1.4 has been also

[1]Although the normalized values for subjective minutiae quality are chosen based on the (possibly arbitrary) values in the NIST templates, other choices may be considered here with possibly different outcomes.

used for MCC template creation and comparisons. The Cumulative Match Characteristic

Table 7.3 – MCC parameters used for latent fingerprint experiments

(a) Cylinder creation

Parameter	Value
R	70
N_S	16
N_D	5
σ_S	7
σ_D	$\frac{\pi}{6}$
μ_Ψ, τ_Ψ	$\frac{1}{500}, 400$
Ω	15
min_{VC}	0.3
min_M	1

(b) Comparison

Parameter	Value
min_{ME}	0.3
δ_θ	$\frac{\pi}{4}$
μ_P, τ_P	$32, 0.25$
min_{n_P}, max_{n_P}	$4, 10$
w_R	0.5
μ_1^ρ, τ_1^ρ	$\frac{1}{24}, -50$
μ_2^ρ, τ_2^ρ	$\frac{\pi}{4}, -15$
μ_3^ρ, τ_3^ρ	$\frac{\pi}{15}, -28$
n_{rel}	2

(CMC) curves (identification rate vs. rank) are shown in Figure 7.1 for the whole database and separately for "Good", "Bad", and "Ugly" images within the NIST SD27 database. Embedding subjective minutiae quality using the proposed quality-based consolidation method improves the overall identification performance by 3 more correct matches (out of 258) in rank-1. Moreover, the improvement for the "Ugly" category is even more notable, for example, the rank-1 identification rate is increased from 65.88% to 68.24% for the "Ugly" set, but from 82.17% to 83.33% for the entire database. The corresponding rank-1 and rank-10 identification rates are separately presented in Table 7.4. In Figure 7.2, two latent fingerprints from the

Table 7.4 – Rank-1 and rank-10 identification rates on NIST SD27 using MCC based comparison without and with embedding subjective minutiae quality

(a) Rank-1 identification rate (%)

Method	NIST SD27	Good	Bad	Ugly
MCC	82.17	95.45	84.71	65.88
MCC+Quality	83.33	96.59	84.71	68.24

(b) Rank-10 identification rate (%)

Method	NIST SD27	Good	Bad	Ugly
MCC	91.47	100	91.76	82.35
MCC+Quality	92.64	100	92.94	84.71

"Ugly" set of NIST SD27 are shown as examples, where embedding quality makes it possible to correctly identify them in rank-1.

7.3.1 Discussion on the statistical significance

Considering the fact that the size of NIST SD27 database is rather small, the improvements obtained in our experiments (reported in Figure 7.1 and Table 7.4) might not be statistically

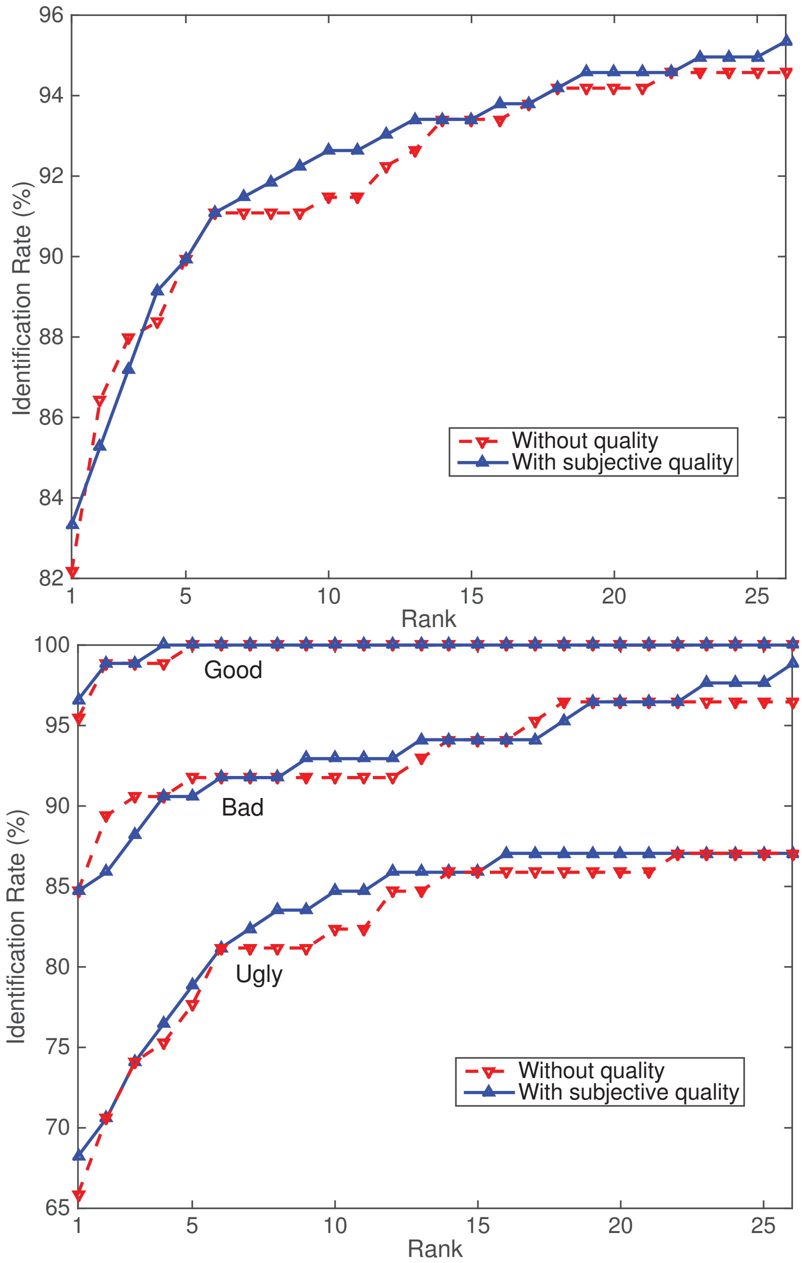


Figure 7.1 – CMC curves showing the identification performance of the MCC based comparison with and without quality embedded, for the entire NIST SD27 database (above) and separately for the "Good", "Bad" and "Ugly" parts of the database (below).

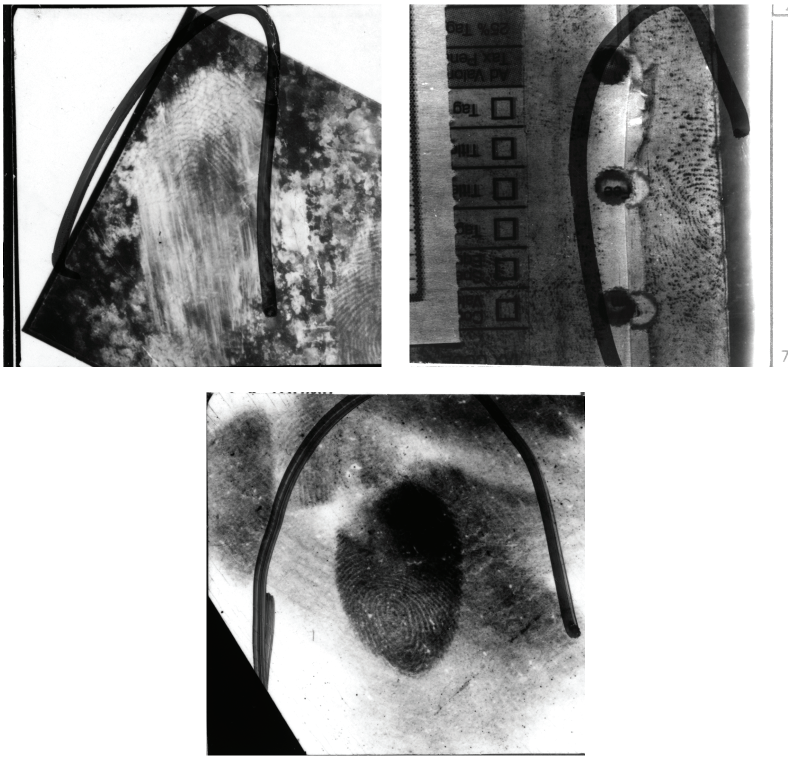


Figure 7.2 – Three latent prints from NIST SD27, which have been correctly identified in rank-1 after (but not without) embedding subjective minutiae quality. The two on top are from the "Ugly" subset and the one underneath is from the "Good" subset.

significant to be generalized. If we look at the rank-1 identification rate ($R1$), we can obtain a confidence interval to evaluate the statistical significance of the results, as follows:.

The rank-1 identification rate ($R1$) is actually defined as the number of correct matches in the rank-1 divided by the total number of matches. Since each match has a binary outcome (for example 1 for correct match and 0 otherwise), then the $R1$ is in fact the arithmetic mean of the outcomes of all the matches in rank-1. Therefore, if we assume the number of correct matches is sufficiently large (usually more than 30), the Central Limit Theorem implies that the $R1$ has approximately a normal distribution with the standard deviation of $\sqrt{\frac{p(1-p)}{n}}$, where n is the total number of matches and p is the probability of a match being correct. Since we do not know the exact value of p, we can use the proportion of correct matches in our database as an estimate for that. In summary, if the estimated rank-1 identification rate is denoted by (p_{R1}), its standard deviation can be estimated as follows:

$$STD_{R1} = \sqrt{\frac{p_{R1}(1-p_{R1})}{n}}, \tag{7.2}$$

where n is the total number of matches. For example, in our experiments on the entire NIST SD27, n is 258 and p_{R1} is approximately 82.17%, then the standard deviation STD_{R1}

is estimated to be 2.38%. If we consider this standard deviation as the error margin, the reported improvement based on rank-1 identification rate falls within this margin and cannot be considered statistically significant. The same statement is hold for different subsets within the database, for example in the "Ugly" subset, the standard deviation is estimated to be $STD_{R1} = 5.1\%$, which is again higher than the reported improvement.

7.3.2 Discussion on the manually marked minutiae

One of the main reasons for failing to significantly improve the latent print identification performance in our experiments might be the fact that we have used the minutiae manually marked by the experts. Such minutiae are already filtered by the experts and only the most relevant ones are remained in the final list. That is also why the experts are not very reliable in assigning a subjective quality to their own annotations.

7.4 Latent palmprint comparison

In this section, we investigate the application of the proposed quality-based consolidation method for embedding local quality measures in latent palmprint comparison. Latent palmprint comparison is the most interesting application of high-resolution palmprint comparison, where minutiae-based methods play a major role. MCC has already shown a very high performance for full-to-full high-resolution palmprint comparisons [17] for example based on the experiments made on the THUPALMLAB database [4]. Therefore, for our experiments we have chosen a more challenging database called Latent Palmprint Identification Database (LPIDB) [87]. This database is publicly available since 2014, and contains 102 full high-resolution palmprint images, together with 380 latent palmprint images which are captured in realistically simulated conditions. The manually marked minutiae are also provided for the latent cases. We perform the experiments based on the simplified cylinder quality measures considered only the quality of the central block as cylinder quality measures. The parameters used for palmprint experiments are summarized in Table 7.5. Figure 7.3 shows the CMC curves comparing the identification performance of each quality feature embedded by the quality based consolidation method proposed in Section 4.2. While the FDA quality measure provides the highest rank-1 identification rate, the GAB quality measure seems to provide better performance on average based on the CMC curves. The RVU and the OF were again the worst quality measures that failed to improve the performance. Regarding the discussion about the statistical significance in Section 7.3.1, the standard deviation on the rank-1 identification rate is estimated to be around 1.92% based on the values corresponding to this database ($n = 380$ and $p_{R1} = 83\%$). This shows that the reported rank-1 identification rates for all quality measures except the RVU and the OF fall within the error margin, and their differences are not statistically significant. Manually marked minutiae in this database can also be a major issue in these experiments, as explained in Section 7.3.2.

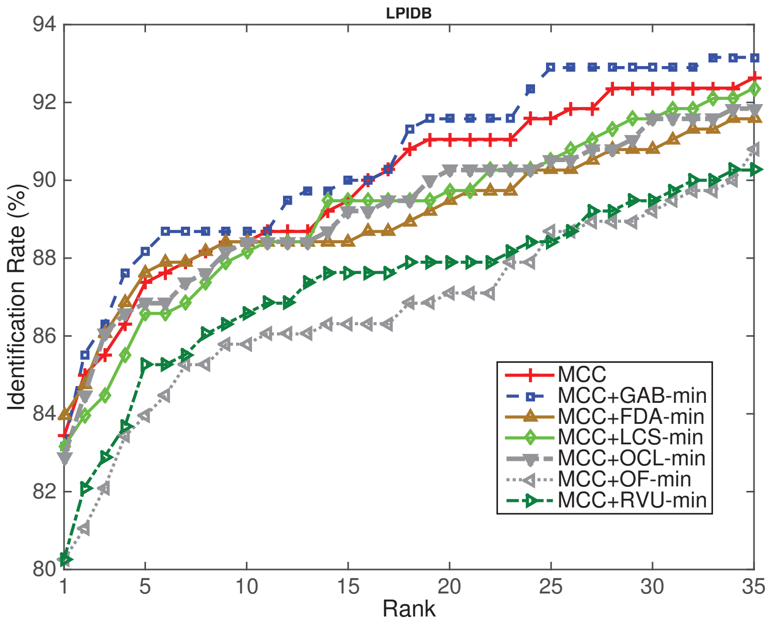


Figure 7.3 – CMC curves comparing the identification performance of the MCC based comparison in presence of several local quality features embedded via the quality-based consolidation method.

Table 7.5 – MCC parameters used for palmprint experiments

(a) Cylinder creation

Parameter	Value
R	90
N_S	16
N_D	5
σ_S	$\frac{28}{3}$
σ_D	$\frac{2}{9}\pi$
μ_Ψ, τ_Ψ	$\frac{1}{100}, 400$
Ω	50
min_{VC}	0.75
min_M	2

(b) Comparison (matching)

Parameter	Value
min_{ME}	0.6
δ_θ	π
μ_P, τ_P	$1500, \frac{1}{100}$
min_{np}, max_{np}	$30, 100$
w_R	0.5
μ_1^ρ, τ_1^ρ	$\frac{1}{18}, -150$
μ_2^ρ, τ_2^ρ	$\frac{\pi}{4}, -15$
μ_3^ρ, τ_3^ρ	$\frac{\pi}{18}, -40$
n_{rel}	11
n_R^{max}	300

8 Conclusions and future work

Data quality can be incorporated into biometric recognition systems at global and local levels for building more accurate systems. Minutiae-based comparison is the most common and foremost technique used for fingerprint recognition and high-resolution palmprint recognition in various security and forensic applications. Beyond that, minutiae-based methods are used in other biometric domains such as hand vein recognition [104, 44]. This thesis was primarily aimed at embedding local quality measures in the modern minutiae-based biometric recognition methods, particularly those based on the MCC [18]. To this end, we introduced the cylinder quality measure to represent the quality of the MCC descriptors, together with several proposals on how to estimate it from local quality features. As explained in Chapters 4 and 5, three new approaches have been proposed at different levels to incorporate local quality measures, such as minutiae quality or cylinder quality, into MCC based comparison. A binary classification model is also proposed to improve the local similarity scores using local quality features. In order to train such a classifier, we need some training data based on the labeled minutiae information. Synthetic fingerprints have been used in this regard as one of the possible options. Finally, the application of the proposed quality-based consolidation method is considered for latent fingerprint and palmprint identification.

Some major findings and observations within the scope of this thesis can be summarized as follows:

- **Cylinder quality measures:**

  1. The central area, i.e., the area closer to the central minutia, plays a major role in quality of each descriptor. That is why, a centralized weighting scheme is generally preferred to the uniform or equal weights for different regions estimating cylinder quality measures.
  2. The existing local quality features are usually rotation invariant, therefore embedding them into the MCC based methods would be compatible with the rotation invariancy of the cylinders.

3. There is a general limitation regarding the issue of quality; that is, the definition of quality is not always clear in the literature, especially when it comes to the local level. For example, one can find several different names by searching about minutia quality, such as reliability, discriminability, confidence, utility, location accuracy, and so on.

- **Embedding local quality measures:**

  1. The proposed discarding approach usually performs better where the density of minutiae is rather high. Therefore, for the cases where there are relatively a small number of minutiae extracted, it is generally not recommended to be used.
  2. The quality-based consolidation method proposed in Section 4.2 is one of the key contributions of this thesis. It is shown through a variety of experiments to improve the recognition performance of the state-of-the-art MCC based methods using various types of local quality measures. An interesting observation regarding this method was that embedding the NBIS MINDTCT minutiae quality into MCC based comparison improved the performance on all real fingerprint databases, but failed to do so on all synthetic databases from FVC2002, FVC2004, and FVC2006.

- **Evaluation of cylinder quality measures:**

  1. The rate of decay for the weights in Eq. 3.4, σ_q, is usually observed to have an optimal value much smaller than the cylinder radius.
  2. Two local quality features, namely Ridge Valley Uniformity (RVU) and Orientation Flow (OF) were almost always the worst candidates in terms of performance in both fingerprint and high-palmprint experiments. They seem to be irrelevant features to be considered in our proposed framework such as for cylinder quality assessments.
  3. For fingerprint, the minutiae quality provided by the FingerJetFX and the Gabor-based quality measures (GAB) were generally among the best candidate features for cylinder quality measures followed by Local Clarity Score (LCS) and Orientation Certainty Level (OCL).

- **Supervised embedding using synthetic fingerprints:**

  1. It is observed in the training set of genuine/impostor MCC pairs that the pair-wise cylinder quality measures seem to be more positively correlated with local similarity scores among genuine MCC pairs than impostor ones.
  2. The supervised embedding model trained using synthetic data could improve the performance for both synthetic and real databases. However, the improvement is more significant for synthetic data, possibly due to the fact that the model is trained on the synthetic data.

- **Latent fingerprint and palmprint identification:**
  1. Embedding subjective minutiae quality via the quality-based consolidation showed some degrees of improvements in the identification performance on NIST SD27 database in rank-1 and higher ranks. However, it is shown that the improvements even in the subsets of the database are not statistically significant, as they fall within the estimated error margin.
  2. None of the local quality features existing for the rolled or plain fingerprints could produce some meaningful quality maps for the latent prints in the NIST SD27. Even using the objective quality measures specifically proposed for latent fingerprints such as the Ridge Clarity Maps [115], we did not achieve any meaningful improvement in identification performance on this database. Manually marked minutiae used in our experiments can be one of the main reasons for this failure, as they are already highly filtered by the experts.
  3. Based on our experiments on the latent palmprints in the LPIDB database, embedding the GAB and FDA quality measures via the proposed quality-based consolidation method has shown some minor, though not statistically significant improvement in the identification performance.

8.1 Future work

Based on the findings and the limitations summarized in this chapter, the following lines of research can be interesting to be pursued:

- **Latent fingerprints:** Developing and optimizing the methods for latent fingerprints is definitely the most challenging direction one can go after this thesis. For example, the objective (local) quality assessment of the latent fingerprints (e.g., those available in the NIST SD27) is an interesting, challenging and rather unsolved problem in this framework. Quality assessment of latent prints still require the intervention of latent examiners.

- **Fusion of local quality measures** Similar to the NFIQ project in global level, the local quality measures could be possibly combined to obtain a new local quality measure. However, gathering a reliable training data similar to what is used for training the NFIQ neural networks seems to be difficult in local levels.

- **Manually labeled data for training and evaluation** Manually labeled data can be more reliable than the synthetic data in a framework similar to what we did for training our logistic regression classifier in Chapter 5.

- **Combination of the embedding methods** The embedding methods proposed in this thesis are at three different levels within the MCC based comparison framework. Therefore, a combination of them might be considered to achieve an even better performance.

Bibliography

[1] Development of NFIQ 2.0. *http://www.nist.gov/itl/iad/ig/development_nfiq_2.cfm*.

[2] FingerJetFX OSE – Fingerprint Feature Extractor, Open Source Edition. *https://github.com/FingerJetFXOSE/FingerJetFXOSE*.

[3] MCC SDK – Version 1.4. *http://biolab.csr.unibo.it/researchPages/download/MCCSdk v1.4.zip*.

[4] Tsinghua University, i-Vision Group: THUPALMLAB palmprint database. *http://ivg.au.tsinghua.edu.cn*, 2011.

[5] F. Alonso-Fernandez, J. Fierrez, and J. Ortega-Garcia. Quality Measures in Biometric Systems. *IEEE Security Privacy*, 10(6):52–62, November 2012.

[6] F. Alonso-Fernandez, J. Fierrez, J. Ortega-Garcia, J. Gonzalez-Rodriguez, H. Fronthaler, K. Kollreider, and J. Bigun. A Comparative Study of Fingerprint Image-Quality Estimation Methods. *IEEE Transactions on Information Forensics and Security*, 2(4):734–743, December 2007.

[7] S. S. Arora, E. Liu, K. Cao, and A. K. Jain. Latent fingerprint matching: performance gain via feedback from exemplar prints. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 36(12):2452–2465, 2014.

[8] D. R. Ashbaugh. *Quantitative-qualitative friction ridge analysis: an introduction to basic and advanced ridgeology*. CRC press, 1999.

[9] J. G. Barnes. Fingerprint sourcebook - chapter 1: History. *http://www.ncjrs.gov/pdffiles1/nij/225321.pdf*, 2010.

[10] O. Bausinger and E. Tabassi. Fingerprint Sample Quality Metric NFIQ 2.0. In *International Conference of the Biometrics Special Interest Group (BIOSIG)*, pages 167–171, September 2011.

[11] S. Belongie, J. Malik, and J. Puzicha. Shape matching and object recognition using shape contexts. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24(4):509–522, April 2002.

[12] S. Bharadwaj, M. Vatsa, and R. Singh. Biometric quality: a review of fingerprint, iris, and face. *EURASIP Journal on Image and Video Processing*, 2014(1):1–28, 2014.

[13] K. Cao, E. Liu, L. Pang, J. Liang, and J. Tian. Fingerprint matching by incorporating minutiae discriminability. In *International Joint Conference on Biometrics (IJCB)*, October 2011.

[14] R. Cappelli. SFinGe: an approach to synthetic fingerprint generation. In *International Workshop on Biometric Technologies (BT 2004)*, pages 147–154, 2004.

[15] R. Cappelli, A. Erol, D. Maio, and D. Maltoni. Synthetic fingerprint-image generation. In *15th International Conference on Pattern Recognition (ICPR)*, volume 3, pages 471–474, September 2000.

[16] R. Cappelli, M. Ferrara, A. Franco, and D. Maltoni. Fingerprint verification competition 2006. *Biometric Technology Today*, 15:7 – 9, 2007.

[17] R. Cappelli, M. Ferrara, and D. Maio. A Fast and Accurate Palmprint Recognition System Based on Minutiae. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, 42(3):956–962, June 2012.

[18] R. Cappelli, M. Ferrara, and D. Maltoni. Minutia Cylinder-Code: A New Representation and Matching Technique for Fingerprint Recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 32(12):2128–2141, December 2010.

[19] R. Cappelli, M. Ferrara, and D. Maltoni. Fingerprint Indexing Based on Minutia Cylinder-Code. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33(5):1051–1057, May 2011.

[20] R. Cappelli, M. Ferrara, and D. Maltoni. Large-scale fingerprint identification on gpu. *Information Sciences*, 306:1–20, 2015.

[21] R. Cappelli, M. Ferrara, D. Maltoni, and M. Tistarelli. MCC: a Baseline Algorithm for Fingerprint Verification in FVC-onGoing. In *International Conference on Control Automation Robotics Vision (ICARCV)*, pages 19–23, December 2010.

[22] R. Cappelli, D. Maio, and D. Maltoni. Synthetic fingerprint-database generation. In *16th International Conference on Pattern Recognition (ICPR)*, volume 3, pages 744–747, August 2002.

[23] R. Cappelli, D. Maio, and D. Maltoni. An improved noise model for the generation of synthetic fingerprints. In *8th Control, Automation, Robotics and Vision Conference (ICARCV)*, volume 2, pages 1250–1255, 2004.

[24] R. Cappelli, D. Maio, D. Maltoni, J. L. Wayman, and A. K. Jain. Performance Evaluation of Fingerprint Verification Systems. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 28(1):3–18, January 2006.

[25] C. Champod. Fingerprint identification: advances since the 2009 National Research Council report. *Phil. Trans. R. Soc. B*, 370(1674), 2015.

[26] C. Champod, C. J. Lennard, P. Margot, and M. Stoilovic. *Fingerprints and other ridge skin impressions.* CRC press, 2004.

[27] J. Chen, F. Chan, and Y.-S. Moon. Fingerprint Matching with Minutiae Quality Score. In S.-W. Lee and S. Li, editors, *Advances in Biometrics*, volume 4642, pages 663–672. Springer Berlin Heidelberg, 2007.

[28] T. Chen, X. Jiang, and W. Yau. Fingerprint image quality analysis. In *Image Processing, 2004. ICIP '04. 2004 International Conference on*, volume 2, pages 1253–1256 Vol.2, October 2004.

[29] Y. Chen, S. C. Dass, and A. K. Jain. Fingerprint quality indices for predicting authentication performance. In *International Conference on Audio- and Video-Based Biometric Person Authentication (AVBPA)*, pages 160–170, July 2005.

[30] D. Clark. ACE-V: Is It Scientifically Reliable and Accurate? *Journal of Forensic Identification*, 52(4):401–408, 2002.

[31] J. Dai, J. Feng, and J. Zhou. Robust and efficient ridge-based palmprint matching. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 34(8):1618–1632, 2012.

[32] J. Dai and J. Zhou. Multifeature-Based High-Resolution Palmprint Recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33(5):945–957, May 2011.

[33] H. Deng and Q. Huo. Minutiae matching based fingerprint verification using delaunay triangulation and aligned-edge-guided triangle matching. In *Audio-and Video-Based Biometric Person Authentication (AVBPA)*, pages 270–278. Springer, 2005.

[34] S. K. Dewan. Elementary, Watson: Scan a palm, find a clue. *The New York Times*, 21:3, 2003.

[35] A. Drygajlo, W. Li, and H. Qiu. Adult face recognition in score-age-quality classification space. In *Biometrics and ID Management*, pages 205–216. Springer Berlin Heidelberg, 2011.

[36] V. Dvornychenko and M. Garris. Summary of NIST Latent Fingerprint Testing Workshop. *National Institute of Standards and Technology, US Department of Commerce, NISTIR 7377*, 2006.

[37] J. Feng. Combining minutiae descriptors for fingerprint matching. *Pattern Recognition*, 41(1):342–352, 2008.

[38] J. Feng and J. Zhou. A Performance Evaluation of Fingerprint Minutia Descriptors. In *International Conference on Hand-Based Biometrics (ICHB)*, November 2011.

[39] Y. Feng, J. Feng, X. Chen, and Z. Song. A Novel Fingerprint Matching Scheme Based on Local Structure Compatibility. In *International Conference on Pattern Recognition (ICPR)*, pages 374–377, 2006.

[40] M. Ferrara, D. Maltoni, and R. Cappelli. Noninvertible Minutia Cylinder-Code Representation. *IEEE Transactions on Information Forensics and Security*, 7(6):1727–1737, December 2012.

[41] F. Galton. *Finger prints.* Macmillan and Company, 1892.

[42] M. D. Garris, C. I. Watson, R. McCabe, and C. L. Wilson. User's Guide to NIST Fingerprint Image Software (NFIS). *National Institute of Standards and Technology, US Department of Commerce, NISTIR 6813*, 2001.

[43] P. Grother and E. Tabassi. Performance of Biometric Quality Measures. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 29(4):531–543, 2007.

[44] D. Hartung, M. Tistarelli, and C. Busch. Vein minutia cylinder-codes (v-mcc). In *International Conference on Biometrics (ICB)*, 2013.

[45] R. A. Hicklin, J. Buscaglia, and M. A. Roberts. Assessing the Clarity of Friction Ridge Impressions. *Forensic Science International*, 226(1):106–117, 2013.

[46] R. A. Hicklin, J. Buscaglia, M. A. Roberts, S. B. Meagher, W. Fellner, M. J. Burge, M. Monaco, D. Vera, L. R. Pantzer, C. C. Yeung, et al. Latent fingerprint quality: a survey of examiners. *Journal of Forensic Identification*, 61(4):385, 2011.

[47] R. A. Hicklin and R. Khanna. The role of data quality in biometric systems. *White Paper. Mitretek Systems*, pages 1–77, February 2006.

[48] D.-S. Huang, W. Jia, and D. Zhang. Palmprint verification based on principal lines. *Pattern Recognition*, 41(4):1316 – 1328, 2008.

[49] G. W. Humphreys, C. J. Price, and M. J. Riddoch. From objects to names: A cognitive neuroscience approach. *Psychological Research*, 62(2-3):118–130, 1999.

[50] M. Indovina, V. Dvornychenko, R. A. Hicklin, and G. I. Kiebuzinski. ELFT-EFS Evaluation of Latent Fingerprint Technologies: Extended Feature Sets [Evaluation #2]. *National Institute of Standards and Technology, US Department of Commerce, NISTIR 7859*, 2012.

[51] M. Indovina, R. A. Hicklin, and G. I. Kiebuzinski. ELFT-EFS Evaluation of Latent Fingerprint Technologies: Extended Feature Sets [Evaluation #1]. 2011.

[52] ISO/IEC 19794-2:2005. *Information Technology – Biometric Data Interchange Formats – Part 2: Finger Minutiae Data.* 2005.

[53] ISO/IEC 2382-37:2012. *Information technology – Vocabulary – Part 37: Biometrics.* 2012.

[54] ISO/IEC 24745:2011. *Information Technology – Security Techniques – Biometric Information Protection.* 2011.

[55] ISO/IEC 29794-1:2016. *Information Technology – Biometric Sample Quality – Part 1: Framework.* 2016.

[56] ISO/IEC TR 29794-4:2010. *Information Technology – Biometric Sample Quality – Part 4: Finger Image Data.* 2010.

[57] M. H. Izadi and A. Drygajlo. Embedding cylinder quality measures into minutia cylinder-code based latent fingerprint matching. In *Proceedings of the ACM Workshop on Multimedia and Security (MMSEC)*, pages 33–38. ACM, 2012.

[58] M. H. Izadi and A. Drygajlo. Estimation of cylinder quality measures from quality maps for Minutia-Cylinder Code based latent fingerprint matching. In *Proceedings of Biometric Technologies in Forensic Science (BTFS)*, pages 6–10, October 2013.

[59] M. H. Izadi and A. Drygajlo. Discarding low quality Minutia Cylinder-Code pairs for improved fingerprint comparison. In *14th International Conference of the Biometrics Special Interest Group (BIOSIG)*, pages 319–326. IEEE, September 2015.

[60] M. H. Izadi and A. Drygajlo. How synthetic fingerprints can improve pre-selection of MCC pairs using local quality measures. In *International Workshop on Biometrics and Forensics (IWBF)*, pages 1–6. IEEE, March 2015.

[61] M. H. Izadi, L. Mirmohamadsadeghi, and A. Drygajlo. Introduction of Cylinder Quality Measure into Minutia Cylinder-Code based Fingerprint Matching. In *IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS)*, pages 353–358, September 2012.

[62] A. K. Jain and J. Feng. Latent Palmprint Matching. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31(6):1032–1047, 2009.

[63] A. K. Jain and J. Feng. Latent Fingerprint Matching. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33(1):88–100, January 2011.

[64] A. K. Jain, P. Flynn, and A. Ross. *Handbook of biometrics.* Springer Science & Business Media, 2007.

[65] A. K. Jain, K. Nandakumar, and A. Ross. 50 years of biometric research: Accomplishments, challenges, and opportunities. *Pattern Recognition Letters*, pages 80 – 105, 2016.

[66] W. Jia, D.-S. Huang, and D. Zhang. Palmprint verification based on robust line orientation code. *Pattern Recognition*, 41(5):1504–1513, 2008.

[67] X. Jiang and W.-Y. Yau. Fingerprint minutiae matching based on the local and global structures. In *15th International conference on Pattern recognition (ICPR)*, volume 2, pages 1038–1041, 2000.

[68] X.-Y. Jing and D. Zhang. A face and palmprint recognition approach based on discriminant DCT feature extraction. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, 34(6):2405–2415, 2004.

[69] F. Kelly, A. Drygajlo, and N. Harte. Speaker verification in score-ageing-quality classification space. *Computer Speech & Language*, 27(5):1068–1084, 2013.

[70] A. Kong, D. Zhang, and M. Kamel. A survey of palmprint recognition. *Pattern Recognition*, 42(7):1408–1418, 2009.

[71] K. Kryszczuk. *Classification with class-independent quality information for biometric verification*. PhD thesis, EPFL, 2008.

[72] K. Kryszczuk and A. Drygajlo. Improving classification with class-independent quality measures: Q-stack in face verification. In *International Conference on Biometrics (ICB)*, pages 1124–1133. Springer, 2007.

[73] A. Kumar and D. Zhang. Personal authentication using multiple palmprint representation. *Pattern Recognition*, 38(10):1695–1704, 2005.

[74] M. J. Leadbetter. Use of automated fingerprint identification systems to process, search and identify palm prints and latent palm marks. *Journal of Forensic identification*, 49(1):18–36, 1999.

[75] J. Li and G. Shi. A Novel Palmprint Feature Processing Method Based on Skeleton Image. In *IEEE International Conference on Signal Image Technology and Internet Based Systems*, pages 221–228, November 2008.

[76] W. Li, D. Zhang, and Z. Xu. Palmprint identification by Fourier transform. *International Journal of Pattern Recognition and Artificial Intelligence*, 16(04):417–432, 2002.

[77] E. Lim, X. Jiang, and W. Yau. Fingerprint quality and validity analysis. In *International Conference on Image Processing (ICIP)*, volume 1, pages 469–472, 2002.

[78] E. Lim, K.-A. Toh, P. Suganthan, X. Jiang, and W.-Y. Yau. Fingerprint image quality analysis. In *International Conference on Image Processing (ICIP)*, volume 2, pages 1241–1244, October 2004.

[79] E. Liu, A. K. Jain, and J. Tian. A coarse to fine minutiae-based latent palmprint matching. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35(10):2307–2322, 2013.

[80] G. Lu, D. Zhang, and K. Wang. Palmprint recognition using eigenpalms features. *Pattern Recognition Letters*, 24(9):1463–1467, 2003.

[81] D. Maio, D. Maltoni, R. Capelli, A. Franco, M. Ferrara, and F. Turroni. FVC-onGoing: on-line evaluation of fingerprint recognition algorithms. *https://biolab.csr.unibo.it/FVCOnGoing/UI/Form/Home.aspx*.

[82] D. Maio, D. Maltoni, R. Cappelli, J. L. Wayman, and A. K. Jain. FVC2002: Second Fingerprint Verification Competition. In *16th International Conference on Pattern Recognition (ICPR)*, volume 3, pages 811–814, 2002.

[83] D. Maio, D. Maltoni, R. Cappelli, J. L. Wayman, and A. K. Jain. FVC2004: Third Fingerprint Verification Competition. In *Biometric Authentication*, pages 1–7. Springer Berlin Heidelberg, 2004.

[84] D. Maltoni, D. Maio, A. K. Jain, and S. Prabhakar. *Handbook of Fingerprint Recognition*. Springer, 2nd edition, 2009.

[85] D. E. Maurer and J. P. Baker. Fusing Multimodal Biometrics with Quality Estimates via a Bayesian Belief Network. *Pattern Recognition*, 41(3):821–832, 2008.

[86] S. Meagher, V. Dvornychenko, and M. Garris. Characterization of Latent Print "Lights-Out" Modes for Automated Fingerprint Identification Systems. *Journal of Forensic Identification*, 64(3):255–284, 2014.

[87] A. Morales, M. A. Medina-Pérez, M. A. Ferrer, M. García-Borroto, and L. A. Robles. LPIDB v1.0 - Latent palmprint identification database. In *IEEE International Joint Conference on Biometrics (IJCB)*, September 2014.

[88] C. Neumann, C. Champod, M. Yoo, T. Genessay, and G. Langenburg. Quantifying the weight of fingerprint evidence through the spatial relationship, directions and types of minutiae observed on fingermarks. *Forensic science international*, 248:154–171, 2015.

[89] NIST Special Database 27. Fingerprint Minutiae from Latent and Matching Tenprint Images. *http://www.nist.gov/itl/iad/ig/sd27a.cfm*.

[90] M. A. Olsen, X. Haiyun, and C. Busch. Gabor filters as candidate quality measure for NFIQ 2.0. In *5th IAPR International Conference on Biometrics (ICB)*, pages 158–163, March 2012.

[91] M. A. Olsen, V. Šmida, and C. Busch. Finger image quality assessment features – definitions and evaluation. *IET Biometrics*, 5:47–64, 2016.

[92] A. A. Paulino, J. Feng, and A. K. Jain. Latent fingerprint matching using descriptor-based Hough transform. *IEEE Transactions on Information Forensics and Security*, 8(1):31–45, 2013.

[93] A. A. Paulino, A. K. Jain, and J. Feng. Latent Fingerprint Matching: Fusion of Manually Marked and Derived Minutiae. In *Conference on Graphics, Patterns and Images (SIBGRAPI)*, pages 63–70, 2010.

[94] D. Peralta, M. Galar, I. Triguero, D. Paternain, S. García, E. Barrenechea, J. M. Benítez, H. Bustince, and F. Herrera. A survey on fingerprint minutiae-based local matching for verification and identification: Taxonomy and experimental evaluation. *Information Sciences*, 315:67 – 87, 2015.

[95] N. Poh and J. Kittler. A Unified Framework for Multimodal Biometric Fusion Incorporating Quality Measures. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 34(1):3–18, January 2012.

[96] N. K. Ratha, R. M. Bolle, V. D. Pandit, and V. Vaish. Robust fingerprint authentication using local structural similarity. In *Fifth IEEE Workshop on Applications of Computer Vision*, pages 29–34, 2000.

[97] A. Sankaran, M. Vatsa, and R. Singh. Latent fingerprint matching: A survey. *IEEE Access*, 2:982–1004, 2014.

[98] L. Shen, A. Kot, and W. Koo. Quality measures of fingerprint images. In J. Bigun and F. Smeraldi, editors, *Audio- and Video-Based Biometric Person Authentication*, volume 2091 of *Lecture Notes in Computer Science*, pages 266–271. Springer Berlin Heidelberg, 2001.

[99] N. Short, A. Abbott, M. Hsiao, and E. Fox. A Bayesian Approach to Fingerprint Minutia Localization and Quality Assessment using Adaptable Templates. In *International Joint Conference on Biometrics (IJCB)*, October 2011.

[100] E. Tabassi, M. A. Olsen, A. Makarov, and C. Busch. Towards NFIQ II Lite. *National Institute of Standards and Technology, US Department of Commerce, NISTIR 7973*, 2013.

[101] E. Tabassi and C. L. Wilson. A novel approach to fingerprint image quality. In *IEEE International Conference on Image Processing (ICIP)*, volume 2, pages 34–37, 2005.

[102] E. Tabassi, C. L. Wilson, and C. I. Watson. Fingerprint Image Quality. *National Institute of Standards and Technology, US Department of Commerce, NISTIR 7151*, 2004.

[103] M. Trauring. Automatic comparison of finger-ridge patterns. *Nature*, 197:938–940, 1963.

[104] L. Wang, G. Leedham, and D. S.-Y. Cho. Minutiae feature analysis for infrared hand vein pattern biometrics. *Pattern recognition*, 41(3):920–929, 2008.

[105] R. Wang. *Palmprint Recognition for Forensic Applications*. PhD thesis, Universidad Autónoma de Madrid, 2013.

[106] R. Wang, D. Ramos, R. Veldhuis, J. Fierrez, L. Spreeuwers, and H. Xu. Regional fusion for high-resolution palmprint recognition using spectral minutiae representation. *IET Biometrics*, 3(2):94–100, June 2014.

[107] R. Wang, R. Veldhuis, D. Ramos, L. Spreeuwers, J. Fierrez, and H. Xu. On the use of spectral minutiae in high-resolution palmprint recognition. In *International Workshop on Biometrics and Forensics (IWBF)*, pages 1–4, 2013.

[108] C. I. Watson, M. D. Garris, E. Tabassi, C. L. Wilson, R. M. McCabe, S. Janet, and K. Ko. NIST Biometric Image Software (NBIS). *http://www.nist.gov/itl/iad/ig/nbis.cfm*.

[109] C. I. Watson, M. D. Garris, E. Tabassi, C. L. Wilson, R. M. McCabe, S. Janet, and K. Ko. User's Guide to NIST Biometric Image Software (NBIS). *National Institute of Standards and Technology, US Department of Commerce, NISTIR 7392*, 2007.

[110] C. E. Wierenga, W. M. Perlstein, M. Benjamin, C. M. Leonard, L. G. Rothi, T. Conway, M. A. Cato, K. Gopinath, R. Briggs, and B. Crosson. Neural substrates of object identification: Functional magnetic resonance imaging evidence that category and visual attribute contribute to semantic knowledge. *Journal of the International Neuropsychological Society*, 15(02):169–181, 2009.

[111] X. Wu, D. Zhang, and K. Wang. Fisherpalms based palmprint recognition. *Pattern recognition letters*, 24(15):2829–2838, 2003.

[112] H. Xu and R. Veldhuis. Spectral minutiae representations of fingerprints enhanced by quality data. In *IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS)*, pages 1–5, September 2009.

[113] H. Xu, R. Veldhuis, A. M. Bazen, T. A. M. Kevenaar, T. A. H. M. Akkermans, and B. Gokberk. Fingerprint verification using spectral minutiae representations. *IEEE Transactions on Information Forensics and Security*, 4(3):397–409, 2009.

[114] S. Yoon, K. Cao, E. Liu, and A. K. Jain. LFIQ: Latent Fingerprint Image Quality. In *IEEE Sixth International Conference on Biometrics: Theory, Applications and Systems (BTAS)*, pages 1–8, 2013.

[115] S. Yoon, E. Liu, and A. K. Jain. On Latent Fingerprint Image Quality. In *Computational Forensics (IWCF)*, pages 67–82, November 2012.

[116] D. Zhang, W.-K. Kong, J. You, and M. Wong. Online palmprint identification. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 25(9):1041–1050, 2003.

[117] L. Zhang and L. Zhang. Characterization of palmprints by wavelet signatures via directional context modeling. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, 34(3):1335–1347, 2004.

Hamed IZADI

Email: mh.izadi@gmail.com, **Phone**: +41 78 868 86 52

Educations

2011 – 2016 **Ph.D.** in Pattern Recognition – **EPFL, Switzerland**
2008 – 2010 **M.Sc.** in Communication Systems – **EPFL, Switzerland**
2003 – 2007 **B.Sc.** in Electrical Engineering – **University of Tehran, Iran**

Honours

- *Excellence scholarship for master studies at the IC School, EPFL 2008-2010*
- *Faculty prize for the 3rd highest GPA among all B.Sc. students of the same class, 2004-2005*

Professional Experience

2011 – 2016 **EPFL, Lausanne, Switzerland**
Doctoral Assistant at Signal Processing Laboratory 5 (LTS5)

2014 – 2014 **University of Bologna, Cesena, Italy**
Visiting Scholar at Biometric System Laboratory (BioLab), 2 months

2009 – 2010 **ABB Switzerland Ltd, Baden-Dättwil**
Intern at IT department, 6 months

Publications

[1] M. Hamed Izadi, and Andrzej Drygajlo. "Improved MCC based comparison via a quality-based consolidation" In preparation, *IEEE Transactions on Information Forensics and Security*, 2016.

[2] M. Hamed Izadi, and Andrzej Drygajlo. "On the use of synthetic fingerprints for embedding local quality features in MCC-based comparison." In preparation, *Pattern Recognition Letters*, 2016.

[3] M. Hamed Izadi, and Andrzej Drygajlo. "Discarding low quality Minutia Cylinder-Code pairs for improved fingerprint comparison." In *International Conference of the Biometrics Special Interest Group (BIOSIG),* IEEE, 2015.

[4] M. Hamed Izadi,, and Andrzej Drygajlo. "How synthetic fingerprints can improve pre-selection of MCC pairs using local quality measures." In *International Workshop on Biometrics and Forensics (IWBF),* IEEE, 2015.

[5] Ahmad Movahedian Attar, M. Hamed Izadi, Maedeh Movahedian, and Shantia Yarahmadian. "Coverage Estimation in Floorplan Visual Sensor Networks." In *Eighth International Conference on Broadband and Wireless Computing, Communication and Applications (BWCCA),* pp. 146-150. IEEE, 2013.

[6] M. Hamed Izadi, and Andrzej Drygajlo. "Estimation of cylinder quality measures from quality maps for Minutia-Cylinder Code based latent fingerprint matching." In *Proceedings of Biometric Technologies in Forensic Science (BTFS)*, pp. 6-10. 2013.

[7] M. Hamed Izadi, Leila Mirmohamadsadeghi, and Andrzej Drygajlo. "Introduction of cylinder quality measure into Minutia Cylinder-Code based fingerprint matching." In *Biometrics: Theory, Applications and Systems (BTAS)*, pp. 353-358. IEEE, 2012.

[8] M. Hamed Izadi,, and Andrzej Drygajlo. "Embedding cylinder quality measures into Minutia Cylinder-Code based latent fingerprint matching." In *Proceedings of the 14th ACM Workshop on Multimedia and Security (MMSec)*, pp. 33-38. ACM, 2012

[9] M. Hamed, Izadi, *Parallel Spread Spectrum MR Imaging*. Master Thesis No. EPFL-STUDENT-149843. 2010

Languages

English – Fluent (spoken & written)
French – Intermediate (B2 level)
Persian – Native speaker

Computer Skills

MATLAB, R, Python, SQL, MS Office, LaTeX.

Hobbies

Swimming, Traveling, Finance, Cooking.