Fingerprint Quality Estimation Using Self-Organizing Maps

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Summary (English)

Fingerprint quality assessment is a crucial task of fingerprint image acquisition process. Modern fingerprint quality assessment algorithms are required to possess high predictive accuracy along with high computational efficiency in order to be used in mobile devices with limited computational resources. Although several quality estimation methods have been proposed, a high computational complexity is attributable to most of them.

The goal of the thesis is to present a novel approach for fingerprint quality assessment based on Self-Organizing Maps as well as to analyze the proposed approach in terms of predictive performance, speed and computational complexity. In the thesis most important aspects of fingerprint quality assessment are covered and an overview of existing fingerprint quality estimation approaches is given. Experimental results presented in this thesis show that SOM network trained on a large data set of feature vectors derived from fingerprint images is capable to distinguish a large number of quality classes and predict utility values for fingerprint samples.

Results of comparative analysis of the proposed and existing fingerprint quality estimation approaches show superiority of proposed approach in terms of computational complexity and speed and show promising results to achieve superiority in the accuracy of quality predictions. This makes the proposed method very attractive to be used in mobile devices based fingerprint identification systems.

Preface

This thesis was prepared at the department of Informatics and Mathematical Modeling at the Technical University of Denmark in cooperation with Center for Advanced Security Research Darmstadt in fulfillment of the requirements for acquiring an M.Sc. in Informatics.

The thesis deals with the problem of evaluation of SOM capabilities towards quality assessment of fingerprint samples.

The thesis consists of 10 Chapters and Appendixes in which a detailed description of the proposed fingerprint quality assessment method, conducted experiments, analysis results and directions for future works are presented.

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Contents

Chapter 1

Introduction

Several questions related to person's identity are asked every day in a variety of contexts: *Has individual access to private information? Is a person searched by the police? Has a person already received benefits from the institution?* Reliable answers for questions such as these are needed by business and public organizations. This raises a need of reliable identity proof mechanisms. As our society becomes more dependent on electronic services, more surrogate representations of identity such as passwords or electronic cards are used in security mechanisms. For systems which require a high security level, these traditional methods do not provide enough protection against identity fraud, and other security threats as passwords and electronic cards are easily transferable among individuals, and there is high risk for them to be stolen or lost. Therefore, identification of individuals is increasingly being based on behavioral and biological characteristics.

Among many biological or behavioral traits, that are used as biometric identifiers for person recognition, fingerprints are the most widespread. Because of their uniqueness, permanency and capture easiness fingerprints have been used for criminal investigations for centuries [PJMM03]. Nowadays, as the demand for automatic identity recognition systems is growing, their application field is continuously expanding.

In recent years several large-scale person identification projects utilizing fingerprints were started in different countries. Significant attention was attracted by the US-Visit program [oHS12] in which fingerprints are being collected from all people visiting United States. Fingerprint data is also used in biometric passports of the European Union countries and all the members of the International Civil Aviation Organization (ICAO) [Org12]. Among the others most significant utilization of fingerprint data is expected by Unique Identification Authority of India (UIDAI) [oI12] which plans to issue Unique Identification (UID) numbers to more than 1.2 billion people living in India.

Recent studies [TWW04] showed that there is a strong relation between the accuracy of biometric system and the quality of fingerprint samples used in it. There is a consensus among academics, business and government organizations that quality of fingerprint images is not attributable only to acquisition settings like resolution, color map, etc., but sample quality is seen as an indicator of error rates associated with the verification or identification of that sample. Therefore, fingerprint quality assessment is considered as a crucial task of biometric enrolment process. For standardization purposes methodologies for objective, quantitative quality score expression, interpretation and interchange have been defined in ISO/IEC IS 29794-1 [ISOa] standard and it is highly advisable for any quality estimation system to follow this standard.

As explicit computation of quality features in fingerprint images remains computationally expensive. This makes incorporation of quality assessment methods in mobile device based biometric systems less attractive. For that reason usage of Self-Organizing Maps (SOM) is a good alternative to all existing fingerprint quality estimation methods.

SOM, also known as Kohonen network, introduced in [Koh90] for more than a decade has been successfully used for various pattern recognition tasks in many research areas and proved to be a robust and efficient algorithm. Unsupervised nature and low computational complexity make this algorithm very attractive for classification of fingerprint image signals. It has been shown that SOM can be successfully used for image classification without any preprocessing steps [GDL+04]. If this approach succeeded on fingerprint images it would let avoid computationally expensive quality feature extraction steps, that exist in all proposed quality assessment methods, making fingerprint quality assessment extremely fast.

This thesis is focused on evaluation of SOM capabilities towards quality assessment of fingerprint samples. The experiments reported in this thesis were mainly implemented to answer the following question: *Can Self-Organized Map trained on a large set of fingerprint images be used as a classifier capable successfully distinguish various quality levels of fingerprint samples?*.

The structure of this thesis can be divided into three parts. In the first part the reader, not familiar with the research field, is introduced to major concepts and definitions of biometrics and fingerprint quality assessment (Chapters 2-4). Second part of the thesis covers a Self-Organizing Map algorithm and concepts associated with it, presenting the reader a SOM based fingerprint quality assessment approach (Chapters 5). The last part covers conducted experiments and their setup, provides a discussion of achieved results and identifies directions for future studies (Chapters 6-10). Additionally a discussion on speedup techniques for the proposed approach and the results of experiments to improve the computational speed of the algorithm are given.

CHAPTER 2

Introduction to Biometrics

The purpose of this and the following chapter is to give a general introduction to the field of biometrics and an overview of related terminology to those readers who are not familiar with this topic so they could follow the discussion of later chapters. Biometrics is in the process of standardization and terms used in this thesis follow definitions established in ISO/IEC[1]

2.1 General terminology

The word *biometrics* is derived from the Greek words bios (meaning life) and metron (meaning measurement) [FZ06]. This term refers to the statistical analysis of *biological* (e.g. fingerprints, face, iris) and *behavior* (e.g. speech, gate) characteristics called *biometric identifiers*, *traits* or *characteristics*. Any human trait can be used as a biometric identifier for recognition purposes as long as it satisfies the following requirements [PJMM03]:

- *Universality* - assumes that every individual possesses this characteristic.

[1] ISO - the International Organization for Standardization. IEC - the International Electrotechnical Commission.

- *Uniqueness* - assumes that any two individuals possessing the trait are sufficiently different.
- *Permanence* - assumes an invariance of the trait over time and persistence of the extracted features. The aging of the individual should not affect the features.
- *Collectability* - assumes the possibility to measure characteristic quantitatively and ensures that this result is reproducible.
- *Performance* - ensures that recognition system based on this biometric characteristic provides a reasonable biometric performance (low errors). Furthermore this property is associated with the time needed to capture the biometric characteristic and to extract features from the captured sample.
- *Acceptability* - defines an extent to which users are willing to accept the biometric identifier in their daily lives. For example, in some cultures, capturing of a certain biometric characteristic can be unacceptable.
- *Circumvention* - assumes big difficulty in replication of biometric characteristic, suitable to fool a sensor.

For referring digital representation of biometric characteristics, a term *biometric sample* is used. Another closely related to biometric sample term is *biometric feature*, which refers to the labels or numbers that are extracted from the sample. The resulting features can be stored in the database as a *biometric template*. If sample is stored in the database without feature extraction it is referred as a *biometric reference*. Biometric sample which is intended for comparison to a biometric reference is referred as a *biometric probe*. [ISOd].

2.2 Biometric recognition

For person authentication, personal features of that person are compared with reference data which can be stored in one of his documents, such as identity card or passport, or in the central database of the system. The aim is to determine whether the biometric characteristic of the person (the *subject*) and the previously recorded representation in the reference data match. Depending on the application context, a biometric system may be used as *verification* or *identification* system [PJMM03]:

- A *verification* system authenticates an individual by comparing the captured biometric characteristic with the previously captured biometric reference or template previously stored in the system. In case of verification system a one-to-one comparison is performed to confirm whether the claim of identity by the individual is true. A verification system can either reject or accept the submitted claim of identity.

- An *identification* system recognizes an individual by performing a search in the entire template database for a match. In case of identification system one-to-many comparison is performed to determine if the individual presents in the database and if so, returns identifier of the biometric reference that matched.

The term *recognition* is used in the biometric field when there is no interest in distinguishing between verification and identification processes. The biometric recognition process can be described with the following steps [Bus09]:

- *Acquisition*: Biometric characteristics are measured by a sensor, camera or other acquisition device creating their digital representation.

- *Feature extraction*: Mathematical transformation is applied to a biometric sample to derive distinguishing and repeatable numbers from the representation. These numbers are a concise representation of the original information. A biometric template is then understood to be a set of biometric features which can be compared directly to biometric features from other presented biometric samples.

- *Enrolment*: Individuals are registered in the biometric system storage.

- *Comparison*: *Probe* sample derived from the live biometric characteristic of one individual is compared against the biometric references of one or more individuals. The result of such comparison is a score that indicates the similarity (a value close but seldom identical to one) or dissimilarity (a value close to zero) of two samples. Several important terms associated with this process are needed to be mentioned. The term *match* refers to a comparison decision that the biometric probe and biometric reference are from the same source. Additionally, the term *impostor* refers to the subject who attempts to be matched to biometric reference of someone else and the term *genuine* refers to the subject, who attempts to be matched to his own biometric reference.

Only after the comparison process is complete the recognition system is capable to decide whether a presented sample matches or non-matches to a stored reference. The biometric recognition process steps are illustrated in figure 2.1. This figure provides a reference architecture for a biometric system ad visualizes the information flow within components of a biometric system, which are: data capture, signal processing, storage, matching and decision.

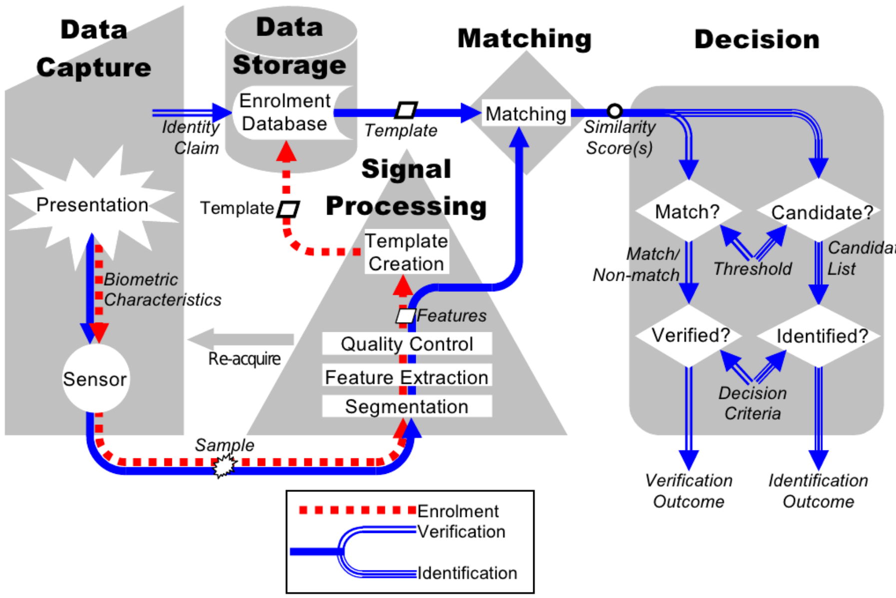


Figure 2.1: ISO reference architecture of the biometric system. Taken from [ISOc].

2.3 Biometric performance

There are multiple failures that can occur in each of the components of biometric system. Depending on the failure type, the performance of the system is evaluated using specific metrics:

- **Failure-to-Capture**. A Failure-to-Capture Rate (FTC) is used, when the capture process could not generate a biometric sample of sufficient quality.
- **Failure-to-eXtract**. A Failure-to-eXtract is used, when the feature extraction process was not able to generate a biometric template. This failure can be caused by insufficient number of features that were identified in the

signal of the trait or by too long feature extraction processing time that exceeds defined limits in the system.

- **Failure-to-Enrol**. A Failure-to-Enrol is used, when the biometric system is not capable to create a biometric reference for data subject. Thus, the Failure-to-Enrol Rate (FTE) expresses the proportion of the population, for which the system fails to complete the enrolment process.
- **Failure-to-Acquire**. The Failure-to-Acquire Rate (FTA) is essential for the verification process and estimates the likelihood that biometric comparison can not be completed due to potential deficiencies in the live sample that is submitted as a probe.

When the biometric system is used for verification it produces *match* or *non-match* decisions depending on whether comparison score exceeds the specified threshold or not. For impostor comparisons a False-Match represents the undesired case that an impostor probe is matching a biometric reference from different subject. Similarly for genuine comparisons a False-Non-Match represents the undesired case that a genuine probe is not matching to biometric reference, which has been created for the same subject from the same source. In relation to this, two types of errors are possible in the system. **False-Match-Rate** (FMR) is identified by ISO/IEC SC37 SD2 [ISOd] as: "*proportion of the completed biometric non-match comparison trials that result in a false match.*" Accordingly **False-Non-Match-Rate** (FNMR) is defined as: "*proportion of the completed biometric match comparison trials that result in a false non-match.*"

In the ideal biometric system impostor and genuine score distributions are well separated. This makes a decision where to set a threshold, separating *match* and *non-match* decisions, straightforward. In such ideal case FNMR and FMR rates are equal to zero. In practice the situation is a bit different and is more similar to the case depicted in fig. 2.2. Usually two score distributions are overlapping, making a decision, whether two samples match or not match, problematic. There is a dependency between FMR and FNMR in every biometric system. If threshold is decreased this makes the system more tolerant to the input variations and noise and increases FMR. On the other hand, if threshold is increased this makes the system more secure and increases FNMR. In such cases in order to evaluate performance of the biometric system it is advisable to look at system performance at all possible values of threshold. This is usually done by plotting *Receiver Operating Characteristic (ROC)* [ZC93] or *Detection-Error Tradeoff (DET)* [MDK+97] curves. Both the ROC and the DET curves are threshold independent which allows to compare different fingerprint systems on a common criterion [PJMM03]. As neither of these two approaches have not been used in the project, a detailed description of DET and ROC curves is left out of scope of this report.

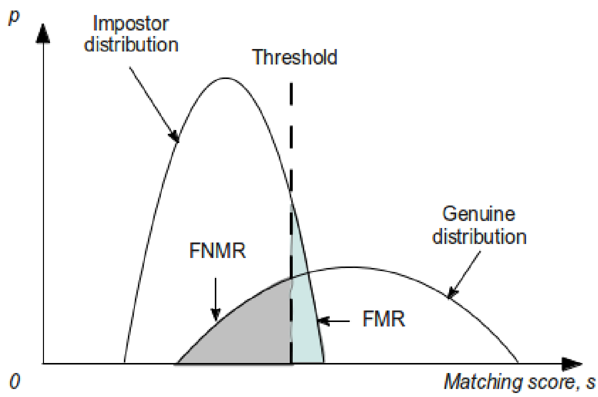


Figure 2.2: FMR and FNMR for a given threshold over the genuine and impostor score distributions.

Chapter 3

Biometric Sample Quality

In biometrics, the term *quality* is used to describe several different aspects of a biometric sample that contribute to the overall performance of a biometric system. In recent years the process of standardization of definitions related to the quality of biometric samples is going. This chapter covers some important terms and models defined in ISO/IEC 29794-1 [ISOa] which let the reader understand the concept of biometric sample quality.

3.1 Biometric sample quality criteria

Many definitions can be associated with the term quality. However, most of the researchers have focused on the definition of quality describing it to be predictive of the utility of features and/or *matchability* of the fingerprint image (fig. 3.1) [PJMM03]. Therefore, quality of a sample is seen as function of such components as character, fidelity and utility, defined as [ISOa]:

- **Character** is an expression of quality based on the inherent features of the source from which the biometric sample is derived. As an example, a scarred or dirty fingerprint has poor character, which makes such sample of a poor quality.

- **Fidelity** is an expression of quality based on the degree of similarity of a biometric sample to its source. Sample fidelity can be seen as a composition of fidelity components derived on the different processing stages of a biometric system.

- **Utility** is an expression of quality reflecting the predicted positive or negative contribution of an individual sample to the overall performance of a biometric system. Utility-based quality is dependent on both the character and fidelity of a sample. Utility-based quality is intended to be more predictive of system performance, e.g. in terms of FMR, FNMR, failure to enrol rate, and failure to acquire rate, than measures of quality based on character or fidelity alone.

The relation between these three quality components can be best understood from the table 3.1.

		Fidelity	
		Low	High
Character	Low	Low fidelity and low character results in low utility. Recapture might improve utility. However, if possible use of other biometric characteristics is recommended.	High fidelity and low character results in low utility. Recapture will not improve utility. Use of other biometric characteristics is recommended.
	High	Samples with high character and low fidelity typically will not demonstrate high utility. Utility can be improved upon recapture or image enhancement techniques.	Samples with high character and high fidelity indicate capture of useful sample. High utility is expected.

Table 3.1: Relationship between character, fidelity and utility. Taken from [ISOa].

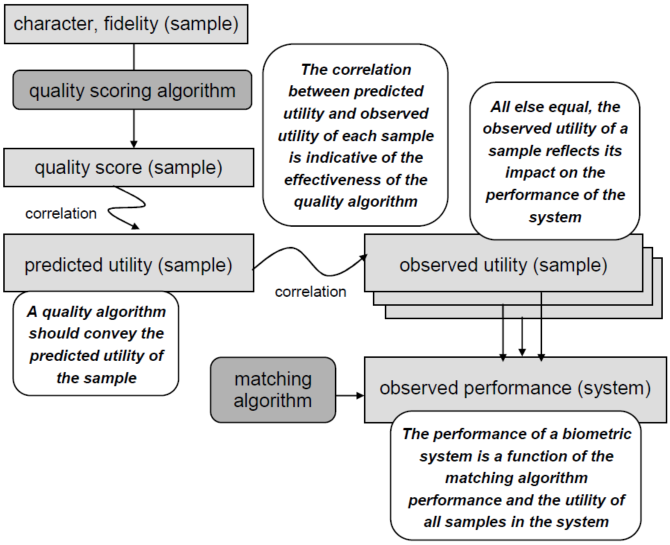


Figure 3.1: Relation between quality and system performance. Taken from [ISOa].

3.2 Application areas of quality data

In order to understand the importance of quality of biometric samples it is necessary to look how this data can be used for overall performance improvement of biometric systems. According to ISO/IEC 29794-1 [ISOa] a quality data of a biometric sample can be used in these application areas:

- **Real-time quality assessment** in which a real-time quality data can be returned by the system in a sample enrolment stage, giving a feedback on quality components of the sample that are of a poor quality.
- **Usage in different applications** in which quality data can be applied for differentiation between quality scores generated by different quality algorithms and capture equipment in order to automatically configure various thresholds for each of these algorithms.
- **Use as a survey statistic** in which quality data can be used for operational quality monitoring of the system.
- **Accumulation of relevant statistics** in which quality scores may be

used to survey users and transactions to accumulate statistics, which later could be used for improvement of quality components of the sample.

- **Reference data set improvement**. In this application area tracking of reference samples and filtering of those which are of a poor quality could improve the performance of overall system.

- **Quality-based conditional processing** in which quality data can be used for different processing of the samples by the system, depending on their quality. For example, a more accurate comparison algorithm could be chosen by the system if sample's quality is considered to be low.

- **Interchange of quality data by disparate systems** in which standardized exchange of quality data can be used in retaining of integrity of quality data in modular architectures of biometric systems.

3.3 Utility-based quality score estimation

As it was described, utility is seen as having correlation both to character and fidelity of biometric samples, as well as to biometric performance (fig. 3.1). For benchmark of different quality assessment algorithms and for overall quality assessment of different data sets it is necessary to have a quantitative representation of utility. In this section a general procedure defined in ISO/IEC 29794-1 [ISOa] is discussed according to which performance based quality score can be assigned to biometric samples .

3.3.1 Numeric utility value computation

For assignment of performance-based quality scores to images containing certain biometric characteristics, a data set with $N_i >= 2$ samples, is considered. It's assumed that each image contains only one biometric characteristic, i.e. one fingerprint or one iris. Samples of each of M subjects are defined as $d_i^{(1)}, d_i^{(2)}, d_i^{(3)}, \dots, d_i^{(N_i)}$, where $i = 1, \dots, M$. The goal of the procedure is to assign scalar quality values $q_i^{(1)}, q_i^{(2)}, q_i^{(3)}, \dots, q_i^{(N_i)}$ to each of the images in the data set. Utility score estimation can be divided into several steps:

1. First, for each of available comparison algorithms defined as $V_k, k = 1, \dots, K$ for each sample $d_i^{(u)}$ a set of genuine comparison scores is generated:

$$S_{ii} = \{s_{i,i}^{u,v} | s_{i,i}^{u,v} = V_k(d_i^{(u)}, d_i^{(v)})\} \tag{3.1}$$

$$u = 1, \dots, N_i; v = u+1, \dots, N_i; i = 1, \dots, M \tag{3.2}$$

In this step a set S_{ii} of $N_i(N_i - 1)$ elements is generated.

2. For each of available comparison algorithms defined as $V_k, k = 1, \dots, K$ for each sample $d_i^{(u)}$ a set of impostor comparison scores is generated:

$$S_{ij} = \{s_{i,j}^{u,v} | s_{i,j}^{u,v} = V_k(d_i^{(u)}, d_i^{(v)})\} \tag{3.3}$$

$$u = 1, \dots, N_i; v = 1, \dots, N_j; i = 1, \dots, M; j = 1, \dots, M; i \neq j \tag{3.4}$$

This results in $\sum_{j=1, j\neq i}^{M} N_j$ impostor comparison scores per sample $d_i^{(u)}$.

3. For every sample $d_i^{(u)}$ an utility value is derived using equation:

$$utility_i^u = \frac{m_{i,u}^{genuine} - m_{i,u}^{impostor}}{\sigma_{i,u}^{genuine} + \sigma_{i,u}^{impostor}} \tag{3.5}$$

where $m_{i,u}^{genuine}$ is the arithmetic mean of sample $d_i^{(u)}$'s genuine comparison scores computed as:

$$m_{i,u}^{genuine} = \frac{\sum_{v=1, v\neq u}^{N_i} s_{i,i}^{u,v}}{N_i - 1} \tag{3.6}$$

and $m_{i,u}^{impostor}$ is the arithmetic mean of sample $d_i^{(u)}$'s impostor comparison scores computed as:

$$m_{i,u}^{impostor} = \frac{\sum_{j=1, j\neq i}^{M} \sum_{v=1}^{N_j} s_{i,j}^{u,v}}{\sum_{j=1, j\neq i}^{M} N_i} \tag{3.7}$$

Analogically, $\sigma_{i,u}^{genuine}$ is the standard deviation of sample $d_i^{(u)}$'s genuine comparison scores computed as:

$$\sigma_{i,u}^{genuine} = \sqrt{\frac{\sum_{v=1, v\neq u}^{N_i} (s_{i,i}^{u,v} - m_{i,u}^{genuine})^2}{N_i - 1}} \tag{3.8}$$

and $\sigma_{i,u}^{impostor}$ is the standard deviation of sample $d_i^{(u)}$'s impostor comparison scores computed as:

$$\sigma_{i,u}^{impostor} = \sqrt{\frac{\sum_{j=1,j\neq i}^{M} \sum_{v=1}^{N_j} (s_{i,j}^{u,v} - m_{i,u}^{impostor})^2}{\sum_{j=1,j\neq i}^{M} N_j}} \tag{3.9}$$

In [NIS12b] several modifications to the described above procedure were proposed, but for purpose of this thesis we will stick to the original procedure proposed in ISO/IEC 29794-1 [ISOa].

3.3.2 Utility binning

Once all utility values have been computed, they can be split into a number of bins corresponding to desired quality classes. In ISO/IEC 29794-1 [ISOa] a simple procedure for division of utility values, which is used in experiments of this this thesis, is proposed. Hereafter this procedure is referred as *utility binning*. Steps included in the procedure are as follows:

1. Computation of two empirical cumulative distribution functions:

$$C(z) = \frac{|\{utility_i^u : (i,u) \in T, utility_i^u <= z\}|}{|\{utility_i^u : (i,u) \in T, utility_i^u < \infty\}|} \tag{3.10}$$

$$W(z) = \frac{|\{utility_i^u : (i,u) \notin T, utility_i^u <= z|}{|\{utility_i^u : (i,u) \notin T, utility_i^u < \infty\}|} \tag{3.11}$$

2. Selection of L, which corresponds to the desired number of bins. For experiments of this thesis number of bins $L = 10$ and $L = 100$ were used.

3. Binning of utility values based on quantiles of the target utility distributions defined by 3.10 and 3.11. An example of the strategy for quantization of utility scores into 5 quality classes is shown in the table 3.2.

3.3.3 Quality score fusion

When quality scores for biometric sample are derived using several comparison algorithms, separate score values are produced by each of used algorithms. The

Bin	Range of target utilities
1	$\{z_i : -\infty < z_i < C^{-1}(0.01)\}$
2	$\{z_i : C^{-1}(0.01) <= z_i < W^{-1}(1)\}$
3	$\{z_i : W^{-1}(1) <= z_i < C^{-1}(x)\}$
4	$\{z_i : C^{-1}(x) <= z_i < C^{-1}(y)\}$
5	$\{z_i : C^{-1}(y) <= z_i\}$

Table 3.2: Utility binning strategy. Taken from [ISOa].

choice of fusion function depends on desirable degree generalization of target quality scores. Hereafter the fusion function application process is referred as *utility fusion*. Several strategies for fusion of utility scores from different comparison algorithms can be identified [ISOa]:

- **Unanimity**: Samples with identical quality assignments from all comparison algorithms become members of the Quality Reference Data set and other samples are simply discarded.
- **Median or other specified percentile point**: Samples with identical quality assignment from more than X percent of K comparison algorithms become members of the Quality Reference Data set. The rest of the sample are discarded.
- **Arithmetic mean**: Final target quality score of each sample will be the arithmetic mean of its quality assignment from all K used comparison algorithms.

CHAPTER 4

Fingerprint Image Quality

In previous chapter the reader was introduced to the concept of biometric sample quality which is seen as a predictor of the matching performance of biometric system. In this chapter the discussion will go further in analysis of quality aspects of such biometric modality as fingerprints. This chapter covers introduction to fingerprint analysis, a discussion of the factors that have an impact on the quality of fingerprint images as well as gives an overview of existing fingerprint quality estimation approaches.

4.1 History of Fingerprint analysis

A fingerprint is defined as a smoothly flowing pattern of alternating valleys and ridges [AAB05](fig. 4.1). Human fingerprints have been discovered on a large number of archaeological artifacts and historical items and this fact shows that in prehistoric times people had already witnessed an individuality of fingerprints [PJMM03]. The awareness of fingerprint individuality had no strict scientific basis until the late seventeenth century, when fingerprints first attracted attention of modern scientists. Since that time fingerprints have been intensively studied.

Figure 4.1: Fingerprint surface. Taken from [PJMM03]

It's worth to mention people, who first started analyzing fingerprints and had most significant impact on the usage of this biometric modality for identification purposes. According to [LG01] the first fingerprint pioneer, who started studying and describing ridges, furrows, and pores on the hand and foot surfaces was English plant morphologist *Nehemiah Grew*. In his publication in 1684 he gave descriptions and functions of ridge detail as well as published extremely accurate drawings of finger patterns and areas of the palm. *Thomas Bewick* was first, who started using an engraving of his fingerprints as a signature. It is very important that this fact took place almost 200 years ago. *Joannes Evanelista Purkinje* was first, who in his thesis in 1823 proposed a concept by which fingerprints could be grouped into nine classes according to configuration of ridges: one arch, one tent, two loops, and five types of whorl. Classification was a major step forward in the use of fingerprints, because it enabled fingerprint to be grouped according to the forms of their patters, thus enabling the search area for matching fingerprints to be minimized. An important advance in fingerprint recognition was made in 1899 by *Edward Henry*, who proposed a fingerprint classification system, also known as "Henry system". The "Henry system" divided all fingerprint forms into 1024 bundles with further sub classification of each bundle. This fingerprint classification system was used up until the end of 20th century and only in recent years has been replaced by ridge flow classification approaches. *Dr. Henry Faulds* was probably the first who experimentally showed immutability of ridge details on a finger. His formulated idea [LG01]:

"When bloody finger marks or impressions on clay, glass, etc., exist, they may lead to the scientific identification of criminals."

can be considered as a starting point of fingerprints usage in criminal investigations.

By the early 20th century, the formation of fingerprints was well understood and major biological principles of fingerprints were formulated [LG01]:

1. Individual epidermal ridges and valleys possess different characteristics for different fingerprints.
2. The configuration types of the ridge-valley patterns are individually variable, but they vary within limits that allow for a systematic classification.
3. The configuration and minutea details of individual ridges and valleys are permanent and unchanging.

Since that time, fingerprint recognition was formally accepted as a valid personal identification method and became standard routine in forensics.

4.2 Automatic Fingerprint Identification Systems

Since discovery of uniqueness of human fingerprints, they have been intensively used in criminal investigations. In order to speedup the search for potential suspects, law enforcement agencies started to collect fingerprints of all criminals. As the size of fingerprint databases was not very large, manual indexing and search for fingerprints in databases was sufficient, but with the constant growth of these databases, new methods to make the search more efficient were needed. Despite the approaches proposed to increase the efficiency of the manual methods of fingerprint indexing and search, the constantly growing demands on manual fingerprint identification quickly became irresistible. Fingerprint search procedures were time-consuming and quite slow. Further, demands raised by painstaking attention needed to visually compare the fingerprints of varied qualities, the monotonic nature of the fingerprint comparison work, and increasing workloads due to a higher a growth of fingerprint databases and demand on fingerprint identification services all prompted the law enforcement agencies to initiate research into acquiring fingerprints through electronic media and automatic fingerprint identification based on the digital representation of the fingerprints. These efforts have led to the development of automatic/semi-automatic fingerprint identification systems (AFIS) over the past few decades [LG01].

By analogy with ISO reference architecture of biometric systems given in figure 2.1, the functional scheme of a typical fingerprint identification system can be constructed (fig. 4.2). AFIS has traditionally consisted of three fundamental subsystems [ISOc]:

1. *data acquisition*: in which the fingerprint signal is captured. Depending on usage scenario of AFIS, a quality inspection of captured samples can be included (and in modern systems this comes as a standard), resulting in scenarios, described in section 3.2;
2. *feature extraction*: in which biometric features are extracted, representing fingerprint image in some space to facilitate comparison;
3. *decision-making*: in which fingerprint template, derived from the sensed image, is compared with a template stored in the system and a likehood of the compared fingerprints, coming from the same subject, is estimated.

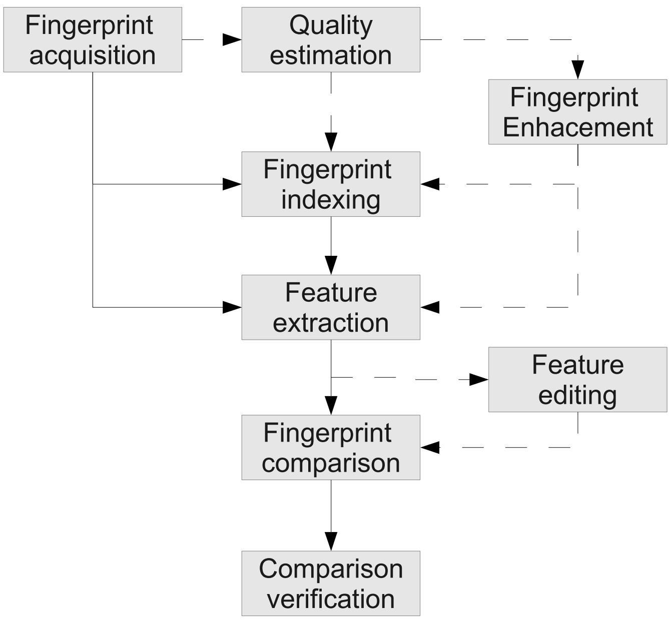


Figure 4.2: Fingerprint identification system

4.2.1 Fingerprint acquisition

Historically, in law enforcement applications, the acquisition of fingerprint images was performed by using *ink-technique* [PJMM03], by which the individual's fingers were smeared with black ink and after rolled on a paper card which was later scanned by general purpose scanner in order to get digital representation of fingerprint (fig. 4.3a). This kind of acquisition process is referred as *off-line*. Nowadays, most AFIS are developed to work with *live-scan* digital images, acquired by directly sensing the finger surface with an electronic *fingerprint scanner*. No ink is required for this approach, and all, that a subject has to do, is to present his finger to a live-scanner [PJMM03].

Nowadays various types of fingerprint scanners are available on the market. These scanners differ as in the way how they are used and in sensing technology they are based on. The detailed observation of various fingerprint sensing technologies is left out of scope of this report, but it is worth to mention, that despite the variety of fingerprint sensing technologies used in modern scanners, the purpose of all such devices remains the same: to keep the fidelity of fingerprint image as close as it possible to characteristics of the original source. An example of fingerprint images, acquired using different sensing technologies, are given in figure 4.3.

4.3 Factors affecting fingerprint image quality

Despite the variety in fingerprint sensing technologies, fingerprint scanners may fail in producing good quality images. Different scanners can better tolerate certain factors that affect the quality of produced images, but the problem of getting images of high quality remains open. Because of this reason, most of modern AFIS still require manual supervision of the quality of scanned images.

Most of the shortcomings in the accuracy of an automatic fingerprint identification systems can be attributed to these factors [UPPJ04]:

- *Inconsistent Contact.* The act of sensing distorts the fingerprint. When finger is being scanned, the three-dimensional shape of it gets mapped onto the two-dimensional surface of the sensor platen. Because the finger is not a rigid object and because the process of projecting the finger surface onto the image acquisition surface is not precisely controlled, various transformations acquire in impressions of a finger. The most problematic of these transformations are elastic distortions of the friction skin of the finger that displace different portions of the finger by different magnitudes and in different directions, making difficult the later comparison of samples. An example of such distortion is depicted in figure 4.4.
- *Non-uniform Contact.* The ridge structure of a finger would be ideally

Figure 4.3: Figerprint images of the same finger acquired using different sensing technologies: a) Off-line scanned fingerprint b) Frustrated Total Internal Reflection (FTIR) scanner, c) Thermal sweep scanner, d) Capacitive scanner, e) Electric field based scanner. Taken from [PJMM03].

Figure 4.4: Misalignment of two genuine samples due to elastic distortion. Taken from [JHPB97].

(a) (b) (c)

Figure 4.5: Three fingerprint images of the same finger with different skin conditions: a) Normal, b) Dry, c) Wet. Taken from [PJMM03].

captured if ridges belonging to the part of the finger are in complete contact with the image acquisition surface and the valleys do not make any contact with this surface. Usually such capture conditions are quite rare and the dryness of the skin (fig. 4.5), shallow/worn-out ridges (due to aging/genetics), various skin diseases, sweat, dirt, and humidity in the air result in non-ideal contact situation. When offline fingerprint scanning is used, an additional factor may include inappropriate inking of the finger; this results in noisy, low-contrast images, which leads to either spurious or missing details in fingerprint samples.

- *Irreproducible Contact.* Manual work, accidents, etc. inflict injuries to the finger can change the ridge structure of the finger either permanently or semi-permanently. Further, each impression of a finger may possibly depict a different portion of its surface. This may introduce additional spurious fingerprint features.

- *Feature Extraction Artifacts.* The feature extraction algorithms are as well imperfect and introduce measurement errors. Various image processing operations can result in loss of fingerprint information and thus result in incorrect extraction of fingerprint features.
- *Sensing.* The act of fingerprint sensing can also add noise to the resulting image. Firstly, there is a loss of information because of quantization process, which takes place as digital images are being produced by scanners. Low scanning resolution or digital image compression can result in loss of fingerprint details. In the live-scan fingerprint acquisition method, dirt or other artifacts from the previous fingerprint capture may also be left behind. A typical imaging system introduces geometrical distortions to the image of the object being sensed due to imperfect imaging conditions. In case of Frustrated Total Internal Reflection sensing, for example, there may be a geometric distortion because the image plane is not parallel to the glass platen [LG01].

4.4 Fingerprint quality assessment

In recent years the problem of fingerprint quality assessment has attracted attention of many scientists, resulting in a large number of publications on this topic ([LJY02], [LTS+04a], [CDJ05], [FKB06], [SKK01], [RB03], [JKCA03], [SWQX04], [LTS+04b], [LTS+04a], [LTS+04b]). An extensive comparative study on suggested quality metrics was performed by Alonso-Fernandez et al. [AFFAOG+07], showing that some of these methods can predict the quality of samples in relation to their impact on biometric performance of the system. Several of these metrics are also included in the ISO/IEC technical report on biometric fingerprint sample quality [ISOb]. Also a good review of existing quality estimation approaches is done in [NIS12a].

According to [AFFAOG+07] all currently existing quality estimation approaches can be roughly divided into three major categories:

1. Exploiting local features of the image;
2. Exploiting global features of the image;
3. Addressing the problem of quality assessment as a classification problem.

In order for the reader to get familiar with the concepts underlying the existing fingerprint quality estimation approaches, in this section some of the methods from each category will be observed.

4.4.1 Local analysis approaches

This type of fingerprint quality analysis is based on examining local structures of the fingerprint which are defined as ridge-valley patterns the fingerprint, taken within a certain local region. To get this kind of local structures, a finger image is partitioned into small blocks, usually having at least 2 clear ridges. Usually, before actual processing of ridge-valey information in the blocks, a segmentation process is performed, by marking blocks as belonging to *foreground* or *background*. This process reduces a number of blocks, which will be used in later processing, resulting in reduced computational costs of the algorithm and more accurate results, as the noise and other non-fingerprint related artifacts are removed from the image.

4.4.1.1 Orientation Certainty Level

The fingerprint pattern within a small area generally consists of dark ridge lines separated with white valley lines of the same orientation. Therefore, consistent ridge orientation and the appropriate ridge and valley structure are considered as distinguishable local characteristics of the fingerprint. The gradient of grey-scale pixel values can be used to analyze such orientation and its strength at the pixel level. The Orientation Certainty Level (OCL) approach proposed in [LJY02] suggested measuring the energy concentration along the direction of ridges using pixel based grey level gradient information within each block.

The steps involved in OCL approach are as follows [NIS12a]:

1. First a Sobel operator [KVB88] is applied to the pixels of each fingerprint block, thus constructing a gradient vector of the image.

2. By performing Principal Component Analysis [Pea01] on the image block gradients, an orthogonal basis for an image block can be formed by finding eigenvalues and eigenvectors. Principal Components Analysis is a multi-variate procedure which rotates the data such that maximum variability is projected onto orthogonal axes. The resultant first principal component contains the largest variance contributed by the maximum total gradient change in the direction orthogonal to ridge orientation. The direction is given by the first eigenvector and the value of the variance corresponds to the first eigenvalue, λ_{max}. On the other hand, the resultant second principal component has the minimum change of gradient in the direction of ridge flow which corresponds to the second eigenvalue, λ_{min}.

   These values can be computed using equations 4.1 and 4.2.

$$\lambda_{max} = \frac{(a+b) + \sqrt{(a - b^2 + 4c^2)}}{2} \tag{4.1}$$

$$\lambda_{max} = \frac{(a+b) - \sqrt{(a - b^2 + 4c^2)}}{2} \tag{4.2}$$

where a, b, c, d are the elements of the covariance matrix C of the gradient vector for an N points image block.

$$C = \frac{1}{N} \sum_N (\begin{bmatrix} dx \\ dy \end{bmatrix} \begin{bmatrix} dx & dy \end{bmatrix}) = \begin{bmatrix} a & c \\ c & b \end{bmatrix} \tag{4.3}$$

3. The ratio *ocl* between the two eigenvalues thus gives an indication of how strong the energy is concentrated along the dominant direction with two vectors pointing to the normal and tangential direction of the average ridge flow respectively.

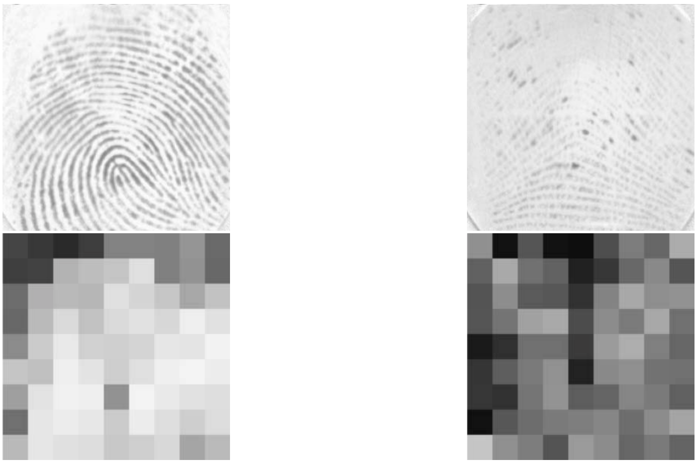
$$ocl = 1 - \frac{\lambda_{min}}{\lambda_{max}} = 1 - \frac{(a+b) - \sqrt{(a-b)^2 + 4c^2}}{(a+b) + \sqrt{(a-b)^2 + 4c^2}} \tag{4.4}$$

ocl value changes in the range $[0, 1]$, where 0 indicates lowest concentration of the energy along ridge-valley direction and can be interpreted as the low quality block (fig. 4.6).

Since the OCL is computed from grey-scale gradient, it can be affected by marks in the sample with strong orientation strength. Also high curvature areas that exist in the center of the fingerprint often do not exhibit a one dominant direction within the block and this can affect the final results of the algorithm. Also, a high computational complexity is attributable to this approach associated with computation gradients and eigenvalues for each of the image blocks.

4.4.1.2 Frequency domain analysis

Locally ridges and values of the fingerprint are being parallel, thus enabling to treat the signature of a high quality fingerprint sample as a periodic signal, which can be approximated by a square wave or a sinusoidal wave as was done in [HAW98]. In the frequency domain, an ideal square wave exhibits a dominant frequency with sideband frequency components. A sinusoidal wave consists of one dominant frequency and minimum components at other non-dominant



(a) Good quality (b) Bad quality

Figure 4.6: Orientation certainty level in each block. High intensity corresponds to high level of certainty. Taken from [NIS12a].

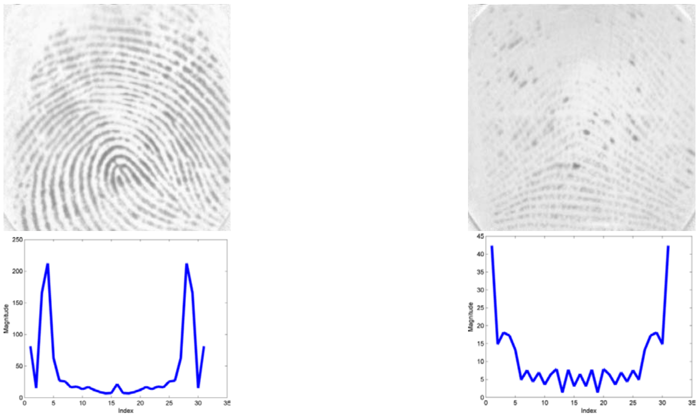
frequencies. The existences of one dominant frequency as well as the frequency of such dominant components are two main elements that are useful in quality determination. The algorithm included in [ISOb] exploits mentioned above idea by extracting signature of the ridge-valley structure in a block-wise manner and computing Discrete Fourier Transform (DFT) to determine the frequency of the sinusoid following the ridge-valley structure.

The steps involved in this quality estimation approach are as follows [NIS12a]:

1. Determination of dominant ridge flow orientation in each of the fingerprint image blocks.
2. Rotation of the block so dominant flow orientation would correspond x axis of the coordinate system.
3. Calculation of the mean pixel intensity value $T(x)$ for the block to extract the ridge-valley structure according to the equation 4.5.

$$T(x) = \frac{1}{2r+1} \sum_{k=-r}^{r} I(x,k) \tag{4.5}$$

4. Calculation the Fourier spectrum of $T(x)$. Given a digital image of size MxN, the two-dimensional Discrete Fourier Transformation (DFT), evaluated at the spacial frequency $(\frac{2\pi k}{M}, \frac{2\pi l}{N})$, is defined by equation 4.6



(a) Good quality **(b)** Bad quality

Figure 4.7: Image blocks with their respective DFTs of the signatures along the ridge direction. Taken from [NIS12a].

$$F(k,l) = \frac{1}{NM} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} I(i,j) \exp^{-i2\pi(\frac{ki}{N}+\frac{li}{M})}, i = \sqrt{-1} \tag{4.6}$$

where $I(i,j)$ refers to the pixel's intensity at the coordinates (i,j) of the image.

5. Discard of the DC component of $T(x)$ and determination of the term F_{max} with the highest magnitude $A(F_{max})$;

6. The final output of analysis is an image quality measure (IQM) computed by equation 4.7.

$$IQM = \frac{A(F_{max}) + 0.3[A(F_{max}-1) + A(F_{max}+1)]}{\sum_{F=1}^{NF/2} A(F)} \tag{4.7}$$

Figure 4.7 shows image blocks with varying quality and their DFT of the signatures derived. As it can be seen images with a good quality exhibit maximum values at a particular frequency range. On the other hand in images of a bad quality the energy concentration of a signal tends to be near 0, which shows that the image doesn't exhibit any frequency information.

High complexity is also attributable to this approach as Fourier transform is a computationally intensive procedure.

4.4.1.3 Ridge-valley Structure analysis

Local Clarity Score (LCS) algorithm proposed in [LTS+04a] represents an example of methods assessing clarity of ridge and valleys. In this approach a linear regression is applied in order to determine a gray-level threshold, classifying pixels as ridge or valley. A ratio of incorrectly classified pixels is determined by comparing with the normalized ridge and valley width of that block.

The steps involved in LCS approach are as follows [NIS12a]:

1. For each of the image blocks V_0 determine dominant ridge flow orientation to create an orientation line which is perpendicular to the ridge flow as shown in figure 4.8;

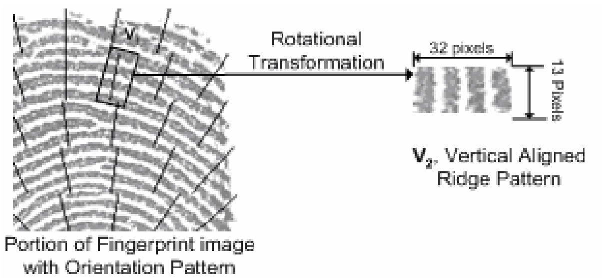


Figure 4.8: Orientation lines according to dominant ridge flow. Taken from [LTS+04a].

2. Align V_0 such that the orientation line is horizontal to create V_1;
3. From V_1 extract a block V_2 which is centered around the orientation line;
4. Compute the average profile V_3 of V_2 using equation 4.8

$$V_3(x) = \frac{\sum_{y=1}^{M} V_2(x, y)}{M} \tag{4.8}$$

where M - size of the block.

5. Determine a threshold DT by applying linear regression on V_3 (fig. 4.9);
6. Determine the proportion of incorrectly classified pixels $\alpha = \frac{v_B}{v_\tau}$ and $\beta = \frac{\rho_B}{\rho_\tau}$ in the ridge and valley regions, where v_B and ρ_B are number of pixels in valley and ridge regions with intensity lower than threshold DT accordingly and v_τ, ρ_τ - total number of pixels in mentioned regions.

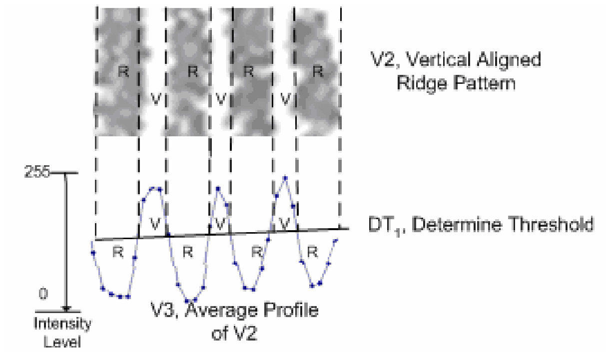


Figure 4.9: Region segmentation according to the threshold. Taken from [LTS+04a].

7. Determine the normalized ridge width and valley width $\overline{W}_r$, $\overline{W}_v$ using equations 4.9 and 4.10.

$$\overline{W}_r = \frac{W_r}{(\frac{S}{125})W^{max}} \tag{4.9}$$

$$\overline{W}_v = \frac{W_v}{(\frac{S}{125})W^{max}} \tag{4.10}$$

where S is a resolution of the image, W^{max} is predicted ridge-valley width in the image and W_r, W_v are observed width values of ridges and valleys.

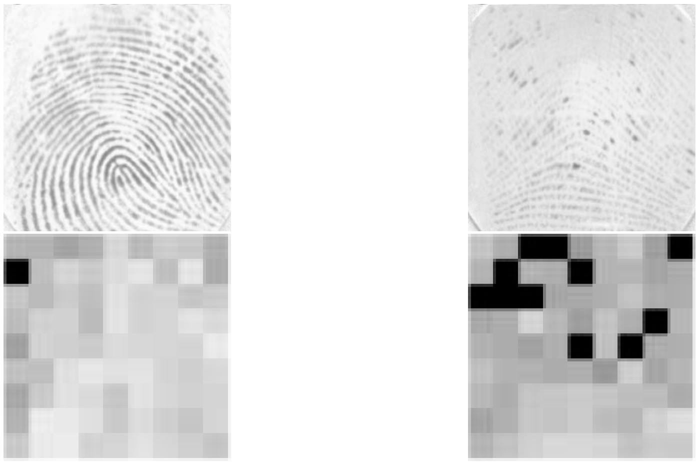
8. The final quality score is computed using the average value of α and β in valid ridge and valley regions according to equation 4.11

$$Q_{LCS} = \begin{cases} (1 - (\frac{\alpha+\beta}{2})) * 100 & (W_v^{nmin} < \overline{W}_v < W_v^{nmax}) \wedge \\ & (W_r^{nmin} < \overline{W}_r < W_r^{nmax}), \\ 0 & \text{otherwise} \end{cases} \tag{4.11}$$

where W_r^{nmin} and W_v^{nmin} are the minimum values for the normalized ridge and valley width, and W_r^{nmax} and W_v^{nmax} are the maximum values for the normalized ridge and valley width.

Figure 4.10 shows the final result of method application on fingerprints of different quality.

Several other fingerprint quality estimation methods, based on analysis of local features, can also be found in [SKK01],[CDJ05], [FKB06].



(a) Good quality (b) Bad quality

Figure 4.10: Map of local clarity scores. High intensity corresponds to high local clarity. Taken from [NIS12a].

4.4.2 Global analysis approaches

Continuity and ridge-valley uniformity are general characteristics of finger images. Continuity is found along the orientation change while uniformity is observed all over the sample for its ridge and valley structure. Each of these characteristics contributes to a standalone global metric. In order to estimate these metrics an analysis of the whole fingerprint structure is needed and this section covers some of the methods, which analyse the overall ridge-valley structure of the fingerprint.

4.4.2.1 Radial power spectrum

The maximum value of the Fourier spectrum is defined as stable in the ridge direction. Since ridges of a finger image can be locally approximated by one sine wave, large value of sine wave energy in a narrow frequency range can represent the strong ridges. This idea is used in Radial Power Spectrum (POW) quality estimation approach included in [ISOb].

The steps involved in POW approach are as follows [NIS12a]:

1. Computation of Magnitute (Power Spectrum) from fingerprint image: $P(k,l) \equiv$

$|F(k,l)|^2$, where $F(k,l)$ frequency domain information of the image defined in equation 4.6.

2. Transformation of Power Spectrum into polar coordinates (fig. 4.11) and normalization to the range $[0,1]$. The normalized magnitude of annular band between two radiuses r and Δ_r in polar Fourier spectrum is computed according to equation 4.12.

$$J(r) = \frac{\sum_{\alpha=0}^{\pi} \sum_{r}^{r+\Delta_r} F(\alpha, r)}{\sum_{\alpha=0}^{\pi} \sum_{r_{min}}^{r_{max}} F(\alpha, r)} \tag{4.12}$$

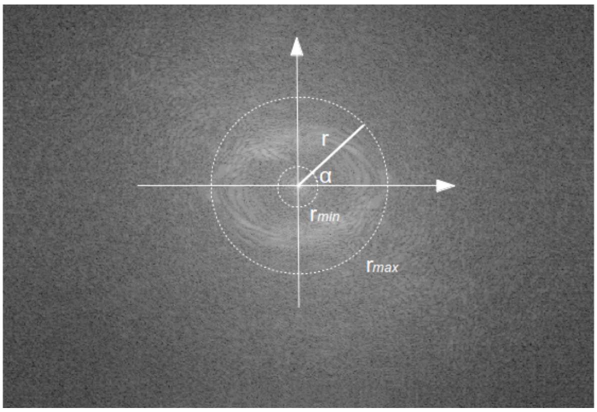


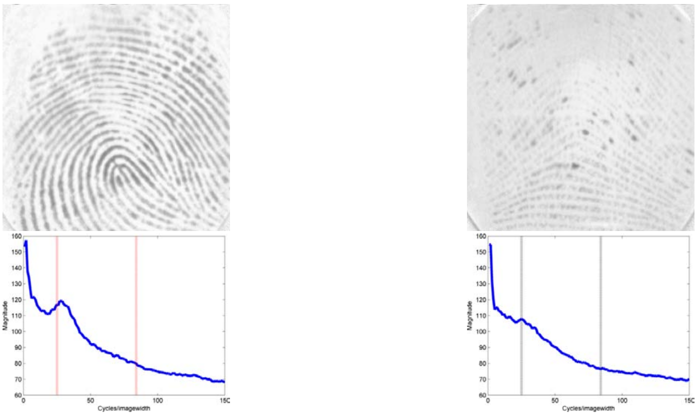
Figure 4.11: Transformation of Fourier spectrum into polar coordinates

3. Computation of final quality score Q_{POW} by finding the maximum energy distribution in radial Fourier Spectrum according to equation 4.13.

$$Q_{POW} = max_{r \in [r_{min}, r_{max}]} J(r) \tag{4.13}$$

Figure 4.12 shows the final result of method application on fingerprints of different quality. In the two bottom figures it can be seen that strong ridges of the pattern result in higher energy values whithin certain frequency range.

Other fingerprint quality estimation methods, based on analysis of global features, can also be found in [LTS+04b] and [OXB].



(a) Good quality **(b)** Bad quality

Figure 4.12: Spectrum with marked frequency of interest. Taken from [NIS12a].

4.4.3 Classification based quality analysis

Classification is a process of identification that is used in all scientific disciplines as a way of comprehending and ordering masses of data. It can be viewed as the process of converting raw data to a categorized meaningful information [AK12].

In the method proposed in [TWW04] the problem of fingerprint quality estimation is considered as a classification problem. Authors look at fingerprint sample quality as at a prediction of the level of separation between genuine and impostor score distributions for chosen sample. The score distribution is defined by equation 4.14

$$o(x_i) = \frac{s(xii) - E[s(xji)]}{\sigma(s(x_{ji}))} \tag{4.14}$$

where $s(x_{ii})$ is genuine comparison score, $E[s(x_{ji})]$ is mathematical expectation of impostor comparison scores for the sample x_i and $\sigma(s(x_{ji}))$ is a standard deviation. Therefore, scalar quality value q_i of the fingerprint sample is considered as a mapping from feature space of sample's characteristics attributable to its quality to the normalized matching score $o(x_i)$ and mathematically described by equation 4.15.

$$q_i = \tilde{o}(x_i) = I(L(v_i)) \tag{4.15}$$

where $\tilde{o}(x_i)$ is predicted value for $o(x_i)$,$L(v_i)$ is feature extraction function and $I(\cdot)$ is the non-linear mapping from sample's quality feature space v_i to the normalized comparison scores space $o(x_i)$. Author's proposed ideas have been implemented in NFIQ fingerprint quality estimation algorithm, which is a part of NBIS package [oST12] developed by National Institute of Standards and Technology, and considered as a "*de facto*" standard approach for fingerprint quality estimation. Also these ideas were used as a basis for the definition and computation of utility-based fingerprint quality scores of the ISO/IEC IS 29794-4 [ISOb] standard, described in section 3.3.

NFIQ algorithm computes a feature vector using the *Quality image map* and minutiae quality statistics by analyzing the fingerprint image and determining areas that are degraded and likely to cause problems. For that reason several characteristics are measured that are designed to convey information regarding the quality of localized regions in the image. These include determination of the *directional flow* of ridges in the image and detection of regions of *low contrast*, *low ridge flow*, and high curvature. Last three conditions represent unstable areas in the image where minutiae detection is unreliable, and together they can be used to represent levels of quality in the image.

Directional flow of ridges represents a fundamental step in the minutiae detection process. The purpose of this map is to represent areas of the image with sufficient ridge structure. Well-formed and clearly visible ridges are essential to reliably detecting points of ridge ending and bifurcation. In addition, the direction map records the general orientation of the ridges as they flow across the image.

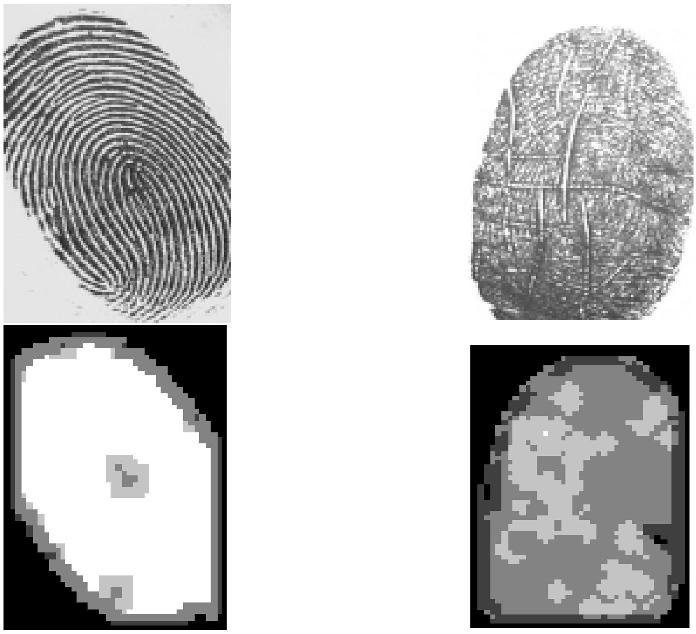
Low contrast map separates the background of the image from the fingerprint, and maps out smudges and lightly inked areas of the fingerprint. Minutiae are not detected within low contrast blocks in the image.

Low flow map marks the blocks that could not initially be assigned a dominant ridge flow. Minutiae detected in low flow areas are not reliable.

High curvature map represents areas of fingerprint image, where detected minutiae points are not reliable. This is especially true at the *core* and *delta* regions of a fingerprint.

The algorithmic description of the construction of mentioned above maps is left out of scope of this report and can be found in [WGT+04]. Figure 4.13

illustrates the resulting quality map, derived by integrating the information of three mentioned above maps into one. The map is visualized as a gray-scale image with black, dark gray, medium gray, light gray, and white corresponding to 5 quality levels, where black color represents background area of the fingerprint image.



(a) Good quality **(b)** Bad quality

Figure 4.13: Two quality maps derived from fingerprint images of different qualities. Taken from [TWW04].

Another important characteristic, used in feature vectors of algorithm is a quality measure of detected minutia points. Two factors are combined in the suggested approach to produce a quality measure. The first factor is taken directly from the location of the minutia point within the quality map. The second factor is based on simple pixel intensity statistics (mean and standard deviation) within the immediate neighborhood of the minutia point which is set to be sufficiently large to contain generous portions of an average ridge and valley. A high quality region within a fingerprint image will have significant contrast that will cover the full gray-scale spectrum. Consequently, the mean pixel intensity of the neighborhood will be very close to 127. For similar reasons, the pixel intensities of an ideal neighborhood will have a standard deviation ≥ 64 [TWW04].

Using this logic, the following reliability measure, R, is calculated given neighborhood mean μ and standard deviation σ:

$$
\begin{aligned}
F_\mu &= 1.0 - \frac{|\mu - 127|}{127} \\
F_\sigma &= \begin{cases} 1.0 & if \sigma > 64 \\ \frac{\sigma}{64} & otherwise \end{cases} \\
R &= min(F_\mu, F_\sigma)
\end{aligned} \tag{4.16}
$$

and Minutia quality, Q, is calculated using quality map level and reliability, as:

$$
Q = \begin{cases} .50 + (.49 * R) & if L = 4 \\ .25 + (.24 * R) & if L = 3 \\ .10 + (.14 * R) & if L = 2 \\ .05 + (.04 * R) & if L = 1 \\ .01 & if L = 0 \end{cases} \tag{4.17}
$$

This results in a quality value on the range 0.01 to 0.99 [WGT+04]. The structure of the final feature vector is summarized in table 4.1.

Number	**Description**
1	Number of blocks that are quality 1 or better
2	Number of total minutiae found in the fingerprint
3	Number of minutiae that have quality 0.5 or better
4	Number of minutiae that have quality 0.6 or better
5	Number of minutiae that have quality 0.75 or better
6	Number of minutiae that have quality 0.8 or better
7	Number of minutiae that have quality 0.9 or better
8	Percentage of the foreground blocks of quality map with quality = 1
9	percentage of the foreground blocks of quality map with quality = 2
10	percentage of the foreground blocks of quality map with quality = 3
11	percentage of the foreground blocks of quality map with quality = 4

Table 4.1: Summary of NFIQ feature vector components

On the second stage of the algorithm constructed feature vectors are used as inputs to a Feed-Forward Artificial neural network classifier. This kind of neural network represents a supervised classification technique. Supervised classification require training areas to be defined by the analyst in order to determine the characteristics of each category to which samples are later assigned by classifier. The output activation level of the neural network is then used to determine the quality value of fingerprint image which is defined in the range [1;5], where 1 is being the highest quality and is 5 being the lowest quality.

Chapter 5

SOM based fingerprint quality estimation framework

Despite the variety of existing fingerprint quality assessment methods, some of which were observed in previous chapter, a high complexity is attributable to most of them. This is also relevant to NFIQ algorithm that, as discussed, has become a standard method for fingerprint quality assessment. In this chapter areas and key factors related to NFIQ algorithm optimization are discussed and as an improvement a new low complexity fingerprint quality assessment approach that employs Self-Organized maps is suggested. This chapter gives an overview to Self-Organizing Map algorithm and observes the main procedures necessary for SOM usage in classification tasks.

5.1 Shortcommings of NFIQ algorithm

While the current NFIQ algorithm remains very reliable, some improvements can be made to it. Areas of the NFIQ algorithm, which require optimization, where highlighted in [OB11] and [MSB10]. Following the discussion in mentioned sources and using a description of the NFIQ algorithm in [TWW04] in this section a short summary of major deficiencies the algorithm is provided:

- The five quality classes scale which is used in the algorithm is quite rough and for certain applications could be insufficient and needs to be extended, preferably to correspond to recommended in ISO/IEC IS 29794-1 [ISOb] scale of 100 quality levels.

- According to [TWW04] 40% of the fingerprint images used for the training of the neural network based classifier were obtained from inked impressions. This type of fingerprint images is not relevant for modern AFIS based on electronic capture devices. A classifier trained on images that are acquired by using different live-scan technologies would be more suitable for most modern fingerprint based identification and verification systems.

- It was reported that for the neural network training of NFIQ algorithm only 3900 fingerprint images were used. In comparison with the size of modern fingerprint databases, which usually contain more than a million of fingerprints, the number of images, which were used for classifier training seems to be insufficient to make it robust enough.

- It was also reported that only three of available commercial SDKs (Software Development Kits provided by various vendors for comparison of fingerprint images) were used for computation comparison scores. Moreover, *Unanimity* strategy (defined in sect. 3.3.3) could discard many fingerprint images from network training and thus could affect the accuracy of resulting classifier. Additionally, such training can be seen as a cause of biased system, which is tuned to a limited number of vendors.

- As it is discussed in section 4.4.3 feature extraction stage of NFIQ algorithm is computationally intensive and this could also have a negative affect if the algorithm would be used in real-time applications.

- Unsupervised nature of classifier used in NFIQ algorithm puts limitation on generalization capabilities of the quality prediction model. Before training of classifier there is a need to have a full comparison scores information for all fingerprint samples used in the training. During the training this information is presented to the model as a desired response, therefore making the model adapt to it. This can introduce a risk of incorrect predictions if available comparison score information contains errors or if a new information becomes available. For example, a new more accurate fingerprint comparison algorithm becomes available and comparison scores produced by this algorithm differ from those, used to train the classifier. In such cases a full retraining of the neural network is needed, which can be a computationally intensive and time-consuming task especially when it is performed on large data sets.

5.2 SOM based alternative to NFIQ

In order to address shortcomings of NFIQ algorithm, in this thesis a new method is proposed that follows ISO/IEC recommendations on fingerprint quality assessment and solves quality classification problem defined in [TWW04] in unsupervised manner using Self-Organizing Maps. Before presenting the actual fingerprint quality assessment approach, an overview of the Self-Organizing Maps algorithm is given.

5.2.1 Kohonen's Self-Organizing Neural Network

The idea of the Self-Organizing Map (SOM) was introduced by Teuvo Kohonen [Koh90], who had a great influence on the development of Artificial Neural Networks (ANNs). Kohonen's Self-Organizing Map has become one of the most popular artificial neural network models for unsupervised learning. This type of artificial neural network requires only an input data set to learn and form its own output representation for a problem. SOM provides two useful operations in exploratory data analysis. These are: clustering that groups data into representative categories, and non-linear data projection in to low-dimensional feature space, preserving topological relations in the patterns. The idea underlying the SOM is based on a model of the human sensory system, which works in such a way that spatial or other relations among stimuli correspond to spatial relations among the neurons [Kia01]. A comprehensive overview of Self-Organizing Maps can be found in [Koh01] and in this section only a brief overview of the most important aspects related to this algorithm are given.

5.2.1.1 SOM architecture

Self-Organizing Map represents a two-layer structure illustrated in figure 5.1. The first layer of this structure represents a group of sensors picking up the data passed to network. This layer is fully connected to the neurons of second layer which is referred as *competitive layer*. With every neuron of competitive layer a parametric *codebook vector* $m_i = [w_{i1}, w_{i2}, \dots, w_{in}] \in R^n$ is associated, components of which represent the strength of connections between two network layers. The second layer represents a regular lattice of neurons set in specific topology. Originally the main purpose of SOM method was in visualization of multidimensional data. For this reason in practice 2 or 3 dimensional lattices of neurons in this layer are most common. However in theory neuron lattices of any dimensionality are possible.

The topology of neurons in competitive layer is defined by the number of neighbors that each neuron of the layer is directly connected to. Two most frequent topology types are *hexagonal*, where each neuron is connected to 6 neighbors in all directions, and rectangular, where neighbors are only identified in horizontal and vertical directions, thus resulting in total of 4 neighbors for each of the neurons 5.2. No evidence of the effect of particular topology type on prediction capabilities of Self-Organizing map was found in the literature, but in [BOB07] and [Koh01] hexagonal topology is identified as more effective for visual analysis and cluster identification on the trained map. In hexagonal lattice all 6 neighbors of each neuron are at the same distance. This way the map becomes smoother making cluster borders on the map more distinguishable.

SOM can be seen as non-linear projection of the probability density function of the high-dimensional input data onto the low-dimensionality display. Let $x \in R^n$ be an input vector. Whenever it passed to the SOM network, it is compared with all the codebook vectors in particular metric d_i. The most commonly used data comparison metric is *Euclidean distance* defined as:

$$d_i = \| \mathbf{x} - \mathbf{m}_i \| = \sqrt{\sum_{j=0}^{N} (x_j - m_{ij})^2} \tag{5.1}$$

A comparative analysis of other possible metrics used in image analysis is done in [HS03], but for the purpose of this project it will be focused on the usage of *Euclidean distance* and later in the report this distance will be referred whenever mentioning distance metric. Thus, the index of the node to which input vector x is mapped whenever it is passed to the network is defined as:

$$c = \underset{i}{argmin}\{\|\mathbf{x} - \mathbf{m}_i\|\} \tag{5.2}$$

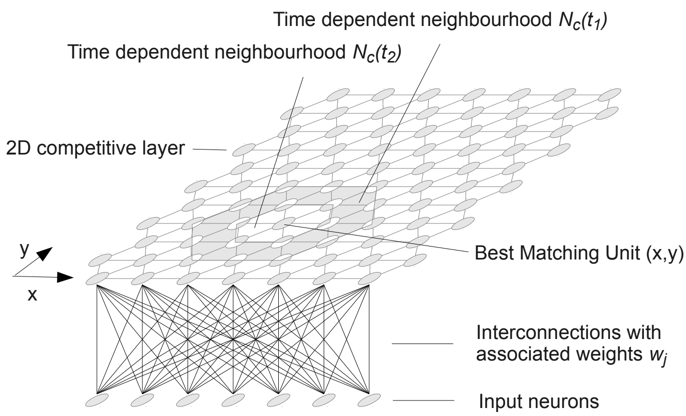


Figure 5.1: SOM architecture

5.2.1.2 Network training

SOM network is trained to learn certain useful features found in input patterns through the unsupervised (competitive) learning process. In *competitive-learning* neurons of the network receive identical input information, on which they compete. With the help of lateral interactions one of the neurons becomes *winner* and by negative feedback it then suppresses the activity of all other cells. During learning, or the process in which the *non-linear projection* is formed, those neurons of the map that are *topographically close in the array up to a certain geometric distance* will activate each other to learn something from the same input. This will result in a local *relaxation* or *smoothing* effect on the codebook vectors in this neighbourhood, which during the learning learning process leads to *global ordering* of information in the map [Koh01]. Thus, a long run presentation of different inputs to the SOM network leads to regional organizations of neurons that become special detectors for different signal patterns.

Before SOM network will be able to recognize different signal patterns, it needs to be trained. Training of the map starts with initialization of codebook vectors m_i. Three different types of network initialization are most common: *random initialization*, *initialization using initial samples* and *linear initialization*. In *random initialization* codebook vectors are simply assigned with random values, preferably of the same scale as input data. Another way to randomly

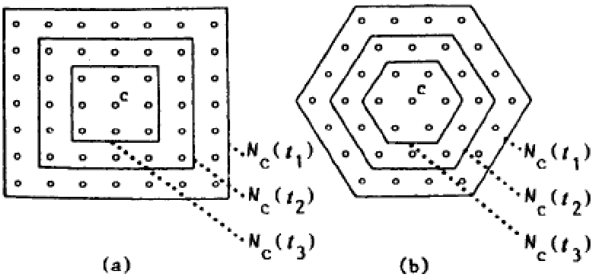


Figure 5.2: Different topologies of SOM competitive layer with marked neighborhood areas. a) Rectangular topology, b) Hexagonal topology. Taken from [Koh01].

initialize codebook vectors of the map is to pick random samples from available input data set and assign their values to codebook vectors. *Linear initialization* is a method that takes advantage of the principal component analysis (PCA) of the input data. In this case values for codebook vectors are selected along two principal eigenvectors of the input data thus making the map to achieve a rough ordering. Linear initialization can improve the speed of map training as the training begins with roughly ordered map. As reported in [Koh01] by using linear initialization at the start of training process codebook vectors of SOM network are being already ordered and therefore much smaller initial neighborhood distance, learning rate values and training steps can be used to achieve the convergence state of the map. On the other hand this approach is computationally intensive as it involves computation of eigenvectors of all input data prior to network initialization process.

After codebook vectors have been initialized training data is passed to the network. The input nodes receive the incoming input data and transmit it to the output nodes via the connections. The activation of the output nodes depends upon the input. In the learning stage, weights of network connections are updated following Kohonen's learning rule:

$$m_{ij}^{(t+1)} = m_{ij}^{(t)} + h_{ci}(x_j - m_{ij}^{(t)}) \tag{5.3}$$

where function $h_{ci}(t)$ is a so-called *neighborhood kernel*, defined over the lattice points. This function determines how strongly the neurons are connected to each other and usually is defined as a two-dimensional function of neighborhood distance and time $h_{ci} = h(\|r_c - r_i\|, t)$, where $r_c \in R^n$ and $r_i \in R^n$ are the radius vectors of nodes c and i respectively, in the array. With increasing $\|r_c - r_i\|$, $h_{ci} \to 0$. Two types of neighborhood kernel are found most frequently in the literature. The simpler kernel function refers to a neighborhood set of array points around node c N_c, whereby $h_{ci} = \alpha(t)$ if $i \in N_c$ and $h_{ci} = 0$ otherwise and $\alpha(t)$ is some monotonically decreasing function of time. This kind of kernel is usually referred as *bubble*, because it relates to certain activity bubbles in laterally connected networks. Another widely applied neighborhood kernel can be written in terms of the Gaussian function,

$$h_{ci} = \alpha(t) \exp(-\frac{\|r_c - r_i\|}{2\sigma^2(t)}) \tag{5.4}$$

where $\sigma^2(t)$ defines the width of the kernel. In this way an update of weights only occurs for the active output node and its topological neighbors within certain distance.

Time dependent *learning rate* function $\alpha(t)$ plays an important role in SOM training. If the learning rate is kept constant, it is possible for weights of codebook vectors to oscillate back and forth between two nearby positions. Therefore this function needs to be decreasing. Very important is a proper choice of initial values of the learning rate and a decreasing speed. Larger initial learning rates make training faster. However if the initial learning rate value is too high, *convergence* state, in which weights of codebook vectors remain stable during the training, may never occur. The same can be said about decreasing speed of the learning rate. If the speed is too slow or too fast this can lead to instability of codebook vectors. Two forms of learning rate functions are commonly used in practice: linear function of time

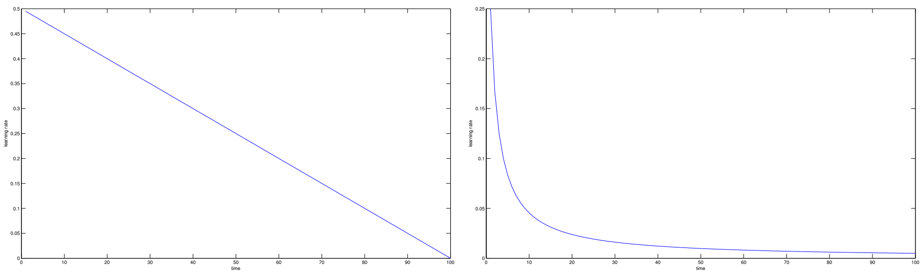
$$\alpha(t) = \alpha_0 \frac{T - t}{T} \tag{5.5}$$

where α_0 refers to initial learning rate and T refers to the total training time, and a function that is inversely proportional to the time

$$\alpha(t) = \alpha_0 (\frac{1}{1 + t}) \tag{5.6}$$

Plots of these two functions are illustrated in figure 5.3. According to [Koh01] there is no mathematical explanation how the choice of particular learning rate function will affect the ordering of neurons in the map and effective choices for these functions and their parameters need to be determined experimentally.

There are two opposing forces in the self-organizing process [Koh01]. Firstly, codebook vectors of SOM network tend to describe the density function of input data. Secondly, local interactions between neurons tend to preserve *continuity*



(a) Linear function **(b)** Inverse time function

Figure 5.3: Learning rates as functions of time.

in the sequences of codebook vectors. A result of these opposing forces is that the codebook vector distribution, tends to approximate a smooth hypersurface and also seeks an optimal orientation and form in the pattern space that best imitates the overall structure of the input vector density.

In general, the reasons for the self-ordering phenomena are very subtle and have been strictly proven only in the simplest cases [Koh01]. For that reason creation of a good self-organized map can be seen as Trail and Error process in which configuration parameters for construction of a good map a searched.

5.2.1.3 Map Quality measures

After SOM network has been trained, it is important to know whether it has properly adapted itself to the training data. Two criterias are considered in evaluation of the quality of trained map:

- How well the input data is classified.
- How well the codebook vectors associated with neurons of the network are ordered.

The first mentioned criteria is associated with a precision of the input data mapping on the competitive layer of the SOM. This describes how accurate is the response of the network to a particular input data. In ideal case when the number of input vectors is equal to the number of neurons in the map it is expected that in converged state each input data sample would activate different neuron on the map. This would mean very high precision of the data mapping. Normally the number of samples on which SOM network is trained is much bigger than the number of neurons in the map. In such cases for estimation of the mapping precision an average quantization error metric could be used [Koh01, p.59]. Average quantization error is defined by equation 5.7.

$$E_q = \frac{1}{N}\sum_{i=1}^{N}\|x_i - w_i\| \tag{5.7}$$

Another mentioned quality criteria of the trained map is associated with the measure of preservation of neighborhood relations. In case of high quality map it is assumed that similar data inputs should activate neighbor neurons on the trained map. Accordingly in the partly converged map similar inputs could activate neurons that are located far away from each other on the map thus indicating a low preservation of neighborhood relations. Several approaches for quantification of neighborhood preservation are suggested in [BP92]. In simplest form this kind of metric can be defined by equation 5.8

$$E_t = \frac{1}{N}\sum_{k=1}^{N}u(x_k) \tag{5.8}$$

where

$$u(x_k) = \begin{cases} 1 & \text{if two first winner neurons for } x_k \text{ are neighbours} \\ 0 & \text{otherwise} \end{cases} \tag{5.9}$$

5.2.1.4 Network calibration

When a sufficient number of input samples has been presented to the SOM network and codebook vectors in the training process have achieved practically stationary values (convergence state), the next step is to perform a *calibration* process of the trained map. This is done in order to locate images of different input patterns on the map. By inputting a number of typical, manually analyzed samples with assigned class values, activated neurons (*winners*) for these samples are labeled with class values. Thus, each neuron of the trained map is now capable to classify signal patterns to which it is trained to respond.

5.2.2 SOM based fingerprint classification

Of all image analysis applications where SOM has been used, those concentrating on texture analysis have been used longest in practice [Koh01]. As fingerprints represent different types of textural information, it is assumed that SOM can be successfully used for analysis of fingerprint data and particularly for grouping of fingerprint images according to the similarities in their represented patterns. It is also assumed that such grouping of fingerprint patterns would identify different fingerprint quality classes and therefore could reflect similar affect of grouped fingerprints on the biometric performance of the system (fig. 5.4).

Following described above SOM network training and calibration procedures it is possible to build classifier capable to recognize and group fingerprint image signals according to their similarities. The only question that remains to be answered is whether such grouping of fingerprint image signals would reflect the quality of corresponding fingerprint images. Therefore, one of the main goals of this study is to find evidence that properly trained SOM classifier without any prior knowledge about the quality of input signals would be able to distinguish a large number of fingerprint quality classes.

Figure 5.4: Identification of similarities in fingerprint patterns leads to a prediction of the affect of fingerprint samples on biometric performance of the system.

Chapter 6

Experimental Setup

This chapter presents a research methodology according to which the research process of this project is build. Along with that a discussion on important aspects related to performed experiments and taken decisions is provided. This includes a description of the data, selected configuration for classifier construction, selection of appropriate error metrics and discussion on SOM based classifier validation methods.

6.1 Research methodology

In this section a methodology that is used throughout the whole research is defined. This methodology represents a sequence of systematic activities that were used as guidelines along the research in order to achieve the study goals defined in section 5.2.2. The purpose of having such methodology was to plan activities and their sequential order, to simplify the analysis process and also to clarify decisions that needed to be made on each of these stages. This ensured a smooth process of the research.

The general scheme of the research framework is illustrated in figure 6.1.

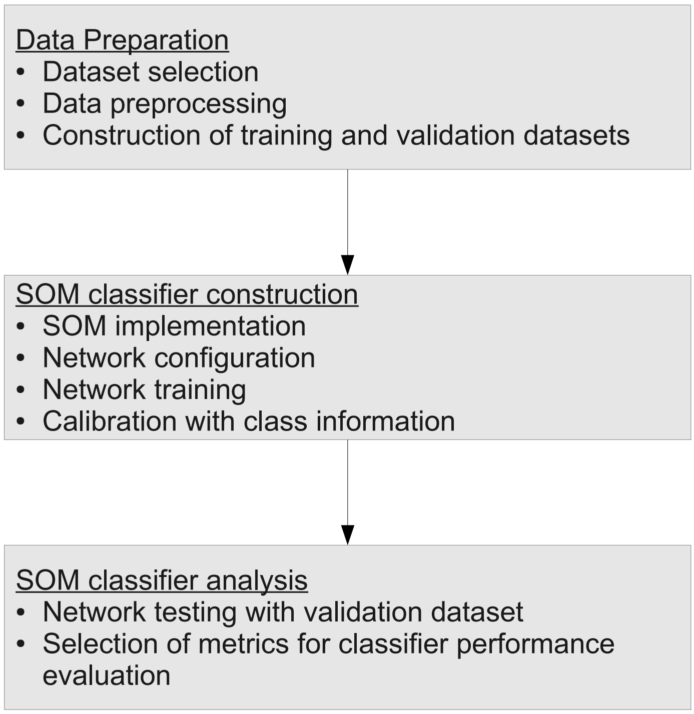


Figure 6.1: Proposed research framework for fingerprint quality assessment using SOM algorithm

Three main stages can be identified in the study of the proposed problem. On the initial stage of the study the data for construction and evaluation SOM classifier is selected and required data sets are constructed. This includes analysis and decision making on what kind of data should be used for classifier construction. Activities that are performed on this research stage include:

- Selection of a proper fingerprint image data set that would be representative enough in terms of variety of fingerprint patterns and their qualities.
- Analysis of the data in order to identify any necessary preprocessing steps for data standardization.
- Construction of training and validation data sets of appropriate sizes and content.

- Estimation of biometric performance based quality scores for the samples in validation and training data sets.

On the second stage a SOM based classifier is constructed using training data set. This stage includes an analysis of proper configuration for classifier construction. Activities that are included on this stage are:

- Choosing of SOM algorithm implementation.
- Selection of initial network configuration parameters: dimensionality of input data, number of nodes in competitive layer of SOM network, the form and topology of this layer.
- Selection of initial training parameters: learning rate, neighborhood size and training length.
- Identification of clusters on the trained map and assignment of appropriate class values to these clusters.

On the last stage of the project an analysis of the constructed classifier is performed. Activities that are defined for this stage of the project are:

- Classification of the samples of validation data set using constructed SOM based classifier.
- Selection of methods and metrics on which performance, accuracy and predictive capabilities of SOM based classifier are evaluated.

6.2 Summary on conducted experiments

All experimental work conducted during the project can be roughly divided into three stages:

- On the first stage of the project it was necessary to prepare and test experimental framework, get familiar with the tools and identify limits of the research. For that reason experiments were conducted on a small set of fingerprint images with the main goal to study SOM network capabilities to group fingerprint images and identify proper network configuration for later experiments. On this stage only visual analysis of trained SOM networks and manual cluster identification was performed. Moreover, it was unclear what kind of fingerprint image information should be used for SOM network training. Therefore, a proper experimental work was needed to identify what sort of information should be used in the training of SOM network in order to achieve a good clustering results for fingerprint images.

- On the second stage of the project the experimental framework was extended with procedures for labeling of trained network nodes with class values, so it was possible to construct and analyze fully functional SOM based classifier. Goals for experiments on this stage can be summarized as follows:

  – Analysis of SOM network capabilities towards prediction of utility scores of different vendors.

  – Analysis of SOM network capabilities towards prediction of fused utility scores.

  To standardize utility scores of different vendors these values were normalized to the range [1,100]. For the fused utility scores a range [1,10] of utility values was chosen. The small scale for fused utility values was used in order to simplify classification accuracy analysis which was performed for each individual utility class.

- On the final stage of the project, when full experimental framework was ready and all necessary values for configuration parameters were identified, SOM based classifier fulfilling all the fingerprint image quality assessment requirements defined in [ISOa] was constructed and analyzed. Goals of experiments performed on this stage can be summarized as follows:

  – Comparison of the SOM fingerprint quality assessment method with other approaches.

  – Comparison of classification results for classifiers trained with different fingerprint image information.

  – Comparison of classification results for classifiers constructed with different configuration parameters.

6.3 Data Preparation

For reliable evaluation of SOM based fingerprint quality assessment, it was important to select appropriate data and conduct any necessary data standardization steps. Several criterias were considered in selection of data sets.

The most important criteria was the size of the data set. It was necessary to get a large-scale data set, which would contain many fingerprints obtained in multiple sessions and that would have high variance in terms of image quality. It was also important that in the selected data set fingerprint images acquired using multiple sensing technologies would be present. This would make the quality assessment approach not bounded to a particular acquisition device.

Currently a number of fingerprint image databases is available at Center for Advanced Security Research Darmstadt (CASED), some of which contain more than 50000 fingerprint samples. Unfortunately due to computational complexity of selected SOM network training methods and problems in available fingerprint comparison algorithms we were not able to obtain reliable comparison score information for most of available at CASED fingerprint data sets. As a result the study was limited to one available data set on which it was possible to conduct a full set of experiments.

6.3.1 Data set selection

In this project two fingerprint data sets were used. On the initial stage, when the only concern was finding features that would let achieve a meaningful fingerprint image clustering by SOM network, it was enough to use relatively small data set. Comparison score information on particular data set on this stage of the project was not needed. For that reason all experiments were conducted using FVC2004 Db2 database. On other stages of the project, when there was a need to perform a more robust analysis of SOM based quality estimation, CASIAFPv5 data set was used.

6.3.1.1 FVC2004 data set

FVC2004 fingerprint image data set was created for international Fingerprint Verification Competition organized in 2004 [tTIFVC12] and is publicly available. As iit is reported the data set consists of four databases (Db1, Db2, Db3, Db4) that were acquired using three different sensors:

- *Db1*: optical sensor "V300" by CrossMatch;
- *Db2*: optical sensor "URU4000" by Digital Persona;
- *Db3*: thermal sweeping sensor "FingerChip FCD4B14CB" by Atmel;
- *Db4*: synthetically generated fingerprints.

(a)

(b)

Figure 6.2: Fingerprint images of the same subject from Db2 database of FVC2004 data set.

Each database of FVC2004 data set contains images of 100 subjects with eight impressions per subject, resulting in 800 impressions in total.

In FVC2004 data set larger intra-class variation was introduced. In different session fingerprints were accured with varying placement of finger on the scanner surface, pressure of finger against the sensor, exaggerating skin distortion and rotation. Additionally, no care was taken to assure the minimum quality of the fingerprints and sensors were not periodically cleaned. Also, the acquisition of different fingers was interleaved to maximize differences in finger placement.

As this thesis considered only analysis of live-scan images, the database Db4 was omitted. Also, as only one larger data set was considered for future experiments, it was tried to conduct experiments on the images similar to those contained in the larger data set. For that reason Db2 database was selected for experiments. Figure 6.2 illustrates an example of fingerprint images contained in Db2 database of FVC2004 data set.

6.3.1.2 CASIAFPv5 data set

CASIA Fingerprint Image Database Version 5.0 (or CASIA-FingerprintV5) [oSIoAC08] contains 20,000 fingerprint images of 500 subjects. As reported the fingerprint images of CASIA-FingerprintV5 were captured using URU4000 fingerprint sensor in one session. The volunteers of CASIA-FingerprintV5 include graduate students, workers, waiters, etc. Each volunteer contributed 40 fingerprint images of his eight fingers (left and right thumb/second/third/fourth finger), i.e. 5

(a) (b) (c) (d)

Figure 6.3: Fingerprint images of the same subject from CASIAFPv5 data set.

images per finger. The volunteers were asked to rotate their fingers with various levels of pressure to generate significant intra-class variations. All fingerprint images are 8 bit gray-level BMP files and the image resolution is 328x356. Figure 6.3 illustrates an example of fingerprint images contained in the data set.

6.3.2 Preprocessing of fingerprint images

As can be seen from the figures 6.3 and 6.2 fingerprints acquired with this type of scanner contain a lot of non-fingerprint related artifacts. This seemed as a major cause of possible incorrect grouping of fingerprints by SOM network when raw pixel intensity values would be used as features for network training. Additionally, incorrect placement and rotation of a finger during the scanning process resulted in fingerprints where ridge-valley pattern was moved too far from the center of the image. In SOM network training process pattern rotation and transition could lead to an assignment of images with similar patterns to different clusters. In order to address this possible problem a procedure of standardization of fingerprint images was developed.

The preprocessing procedure that ensured accurate removal of any non-fingerprint pattern related artifacts and proper placement of the patterns in the image can be summarized in these steps:

- Image segmentation using Gabor filters.
- Combination of erosion an inverse erosion processes on segmentation mask.
- Image centering
- Removal of areas incorrectly segmented as foreground in the image

- Erosion of segmentation mask.
- Cropping of the image to minimal height and width of the whole data set.
- Identification of the largest area in segmentation mask and removal of other areas which are considered belonging to the image background.

In the first step a response from Gabor filters of four orientations is used to build a segmentation mask. The general form of a complex 2D Gabor filter in the spatial domain is given by equation 6.1.

$$h_{Cx}(x, y, f, \theta, \sigma_x, \sigma_y) = \exp\left(-\frac{1}{2}\left(\frac{x_\theta^2}{\sigma_x^2} + \frac{y_\theta^2}{\sigma_y^2}\right)\right)\exp\left(j2\pi f x_\theta\right), \tag{6.1}$$

where

$$\begin{aligned} x_\theta &= x\sin\theta + y\cos\theta \\ y_\theta &= x\cos\theta - y\sin\theta \end{aligned}$$

f is the frequency of the sinusoidal plane wave along the orientation θ, and σ_x, σ_y are the parameters of the Gaussian window.

filter frequency f is seen as the reciprocal of the average inter-ridge distance. For fingerprint images captured from an adult population with the 500dpi resolution, the average inter-ridge distance is approximately 10 pixels [JPHP00]. Therefore, value $f = 0.1$ was set for experiments.

Parameters for four different filter orientations were set as $n = 4$, $\theta = (k - 1)/n\pi, k = 1, \ldots, n$, respectively. The Gaussian parameters were set as $\sigma_x = 6.0$ and $\sigma_y = 6.0$.

Experimental results on selected data set showed that Gabor filter based segmentation of fingerprints was not accurate enough. To compensate shortcomings of Gabor segmentation and remove incorrectly segmented areas of the image additionally an erosion process was used. Application of erosion on segmentation mask resulted in loss of information on the edges of fingerprint patterns but let remove most of incorrectly segmented areas. This was considered as not having serious affect on final classification results because usually the central part of fingerprint pattern contains most information for fingerprint analysis.

After image has been segmented a center of gravity is calculated over the segmented area and the whole image is moved so the center of gravity of the fingerprint image would correspond to the center of the actual image. This ensures that all fingerprints are positioned at the center of the image. Experiments showed that after centering of the image additional artifacts could appear on the image. For their removal an erosion process was applied on segmentation mask.

For SOM network training all feature vectors must be of same dimensionality. To ensure that feature vectors constructed by the procedure described in 6.4.1 have same dimensionality cropping of the images from training data set is performed so dimensions of each image would correspond to minimal height and width of all used images.

On the next step detection of the largest segmented area is performed in the image. This area is assumed to be the area of fingerprint pattern and all other areas are masked.

Results of the described preprocessing procedure are illustrated in figure 6.4

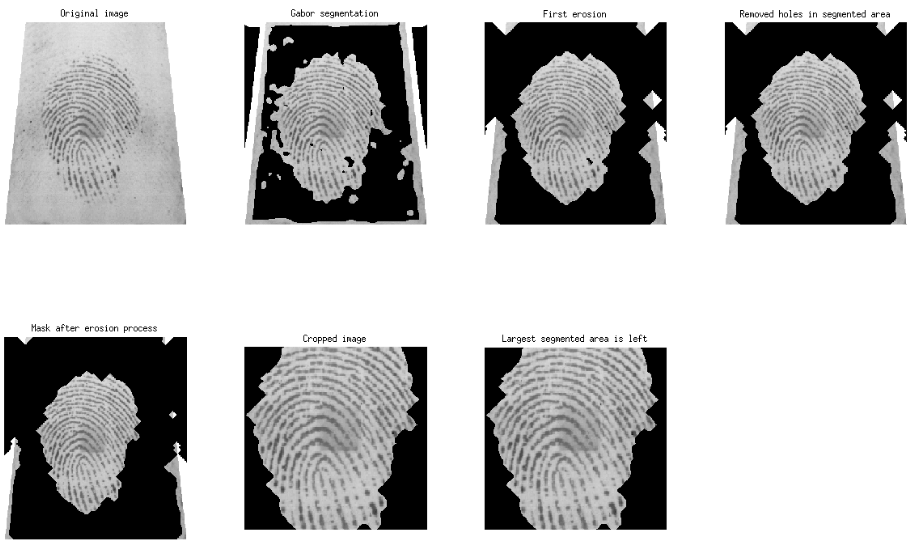


Figure 6.4: Preprocessing steps applied on fingerprint image

6.3.3 Training and validation data sets

In this project a *Train-and-test* neural network validation model was used [TS96]. This is the most common method of neural network based model construction and validation and assumes division of available data set into two sets.

One of newly constructed sets is used for model construction (training of SOM network), while the other is used to validate this model.

One of the goals for this study was to have the quality prediction model built using much larger data set comparing with the one used in NFIQ approach. Therefore, the proportion of available fingerprint images set aside for training was set to 66% or 13333 images. Accordingly the proportion of available fingerprint images set aside for validation was set to 33% or 6667 images. Construction of mentioned data sets was performed by random selection of defined numbers of images from initial data set.

On later stages of the project an observation was made that training and validation sets contained fingerprint images of the same fingers. To eliminate the possible affect of this fact on the final model, when similar patterns would be used in model training and validation, two sets were rebuilt, which resulted in 13361 and 6639 images in training and validation sets accordingly.

6.3.4 Utility computation

Currently at CASED fingerprint comparison algorithms of three different vendors are available. These algorithms with assigned id numbers *28*, *63* and *83* were used for utility score computation for every fingerprint sample in validation and training data sets using the procedure described in section 3.3. Later these values were used as class labels in calibration process of SOM network. Experiments were performed with utility values of each individual vendor as well as with the values produced by fusing utilities of all vendors into one meaningful quality score value.

6.4 SOM network construction

6.4.1 Construction of feature vectors

In order to use SOM network for recognition of fingerprint patterns, the network had to be trained with information representing these patterns. In pattern recognition and machine learning such kind of information representing an object is usually referred as a *feature vector* and represents an n-dimensional vector of numerical features. One possibility for feature vector construction is to use quality metrics observed in 4.4 as vector components. Analogical approach for

SOM training was already considered in [LTS+04b]. In this project such approach was considered unsuitable because with it would be impossible to fulfill one of the requirements for the fingerprint assessment method to be of low computational complexity. Moreover SOM fingerprint quality estimation approach was seen as an alternative to all mentioned before quality estimation method. Therefore the main focus in the project was put on working with raw data of fingerprint images. Usage of raw image data for construction of feature vectors didn't require any computationally intensive procedures and was seen as the most computationally efficient way of representing the image. For comparison purposes several experiments were also conducted using Fourier transform based fingerprint image features.

6.4.1.1 Feature vector construction using raw image data

In this approach every pixel of fingerprint images is considered as a separate feature representing the image and is used in SOM classifier training. Thus, feature vector construction with this kind of data is straight forward and includes transformation of image data to one dimensional array as illustrated in 6.5. This can be done by placing in one row pixels of every column in the image. While all images used in SOM network training and validation are processed in similar way and information of every pixel in the image is included in feature vector, the actual procedure how feature vector is constructed from raw pixel values is not important.

Usage of described approach on fingerprint images of CASIAFPv5 data set of size 364x328 resulted in feature vectors with dimensionality equal to 119392. Such size of feature vectors put additional computational and resource demands on network training process. On the other hand as this this process was performed offline resource and computational complexity of this approach was not considered as a problem.

Additionally usage of input vectors of such high dimensionality, put some limitations on the way how codebook vectors of SOM network could be initialized. As discussed in section 5.2.1.2 there are two basic ways for initialization of codebook vectors in SOM network:random initialization and linear initialization. However, tests with implementations of SOM algorithm disscussed in section 6.4.2 showed that linear initialization puts high demands on the memory resources and therefore can not be used with input vectors of very high dimensionality.

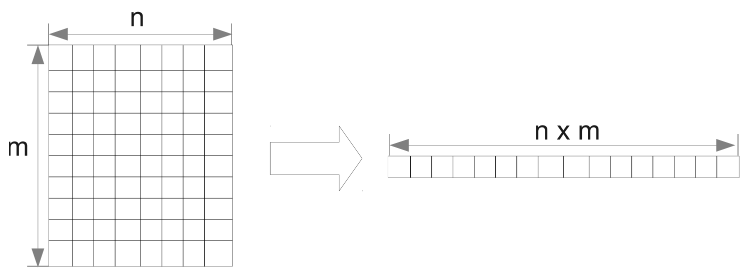


Figure 6.5: Image data transformation into the feature vector

6.4.1.2 Feature vector construction using Fourier transform based features

In this approach feature vector construction was based on the method proposed in [TA06]. In this method feature estimation is performed on the squared area of the fingerprint image. For that reason fingerprint images of rectangular form are first cropped. For this study the size 240x240 for the cropped area was chosen as the area of such size covered most of the fingerprint pattern in the image. After squared area is cropped, it is divided into four equal non-overlapping parts as illustrated in figure 6.6. Each of non-overlapping images of size 60x60 pixels is transformed to frequency domain with DFT algorithm. After that all FFT coefficients of the image are divided into four groups, where each group is subdivided into three levels according to the scheme illustrated in figure 6.7. To create a feature vector components, the standard deviation of the FFT coefficients from four different groups with the same number is computed. For example, to obtain the first parameter in the feature vector, the standard deviation of the FFT coefficient values in the area 1A, 1B, 1C and 1D is calculated. Since the FFT coefficient values contain both real and imaginary parts, their absolute values are used for computation of feature vector components. Mentioned above procedure results in a feature vector of 9 compoents.

6.4.2 SOM implementation

For this project it was decided to work with available implementations of SOM algorithm instead of doing an implementation by ourselves. Tested implementations of SOM algorithm included:

(a) Cropped area (b) Quartered images

Figure 6.6: Image transformation in FFT based feature vector construction approach

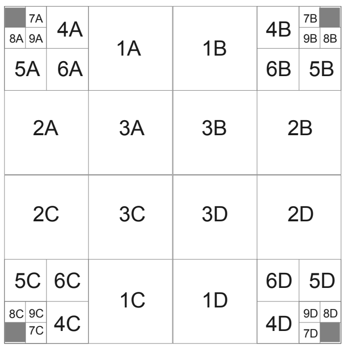


Figure 6.7: Subgrouping of FFT coefficients

1. SOM implementation found in *MatLab Neural Network Toolbox.* Neural Network Toolbox of MATLAB programming environment for algorithm development, data analysis, visualization, and numerical computation provides tools for designing, implementing, visualizing, and simulating of neural networks. [Mat12].

2. *SOM_PAK* software package. The SOM_PAK [KHKL96] program package contains all programs necessary for the correct application of the Self-Organizing Map algorithm in the visualization of complex experimental data. As reported the first version of this program package was published in 1992 and since then the package has been updated regularly to include latest improvements in the SOM implementations. The last version of the

program package was published in 1996. This package is publicly available in open source and licensed for any modifications for academic purposes.

3. *SOM toolbox* software package for Matlab. The "SOM Toolbox" project [oTLoCS] [VHAP99] was initialized back in 1997. SOM Toolbox is a software library for Matlab 5 (version 5.2 at least) implementing the Self-Organizing Map (SOM) algorithm. The package was released with intention to complement the SOM_PAK program package as matlab environment provides more flexibility. This package is publicly available in open source and licensed for any modifications for academic purposes.

A comprehensive study of mentioned software packages showed that SOM implementation provided in Neural Network Toolbox of Matlab was very slow and resource demanding when feature vectors of high dimensionality were used for network training. Due to the high demands on operating memory with available computational resources it was only possible to perform training of quite small maps using this SOM implementation.

The same problem was faced by performing experiments with SOM Toolbox software package. This left us with only one implementation of SOM algorithm that after a number of tests showed to be suitable for SOM training using high dimensionality feature vectors and fully satisfying our needs.

6.4.3 Network training

An important task for SOM network training is the choice of training parameters and determination of the state when the training process can be stopped. For this task usually a *Trial and Error* process is employed, as there are no analytic ways to determine parameters for training of a good map for a particular data set.

6.4.3.1 Selection of training parameters

It was decided to follow recommendations for a good Map construction given in [Koh01] by dividing the network training process in two phases. According to recommendations, in the first phase relatively large initial learning rate and neighborhood radius are used. In the second phase both learning rate and neighborhood radius are small right from the beginning. This procedure corresponds to first tuning the SOM approximately to the same space as the input data and then fine-tuning the map.

For the first phase initial learning rate of 0.5 was chosen, and 0.05 for the second phase. Neighborhood radius starts from $max(mapsize)/4$ and goes down to one fourth of that (unless this would be less than 1). On second phase, neighborhood radius starts from where it stopped in first phase, and goes down to 1. The length of second phase is 4 times bigger that of the first phase.

By performing a number of experiments using quantization error metric described in section 5.7 for map quality estimation it was seen that such scheme gives a better input data mapping results input with the straightforward training network training process consisting of only one phase.

6.4.3.2 Convergence state estimation

With a converged status, SOM can characterize the distribution of input samples, and thus generate a low-dimensional map from a multi-dimensional feature space. A well-trained SOM successfully preserves continuity in the mapping from the SOM grid to the data space.

In order not to change too many network parameters the convergence state of the map was determined by using the initial training parameters from previous section with varying training length and quantization error metric for convergence state estimation. Experimentally it was determined that with the total training length of 1000000 iterations for every feature vector construction method the error metric remained stable and extension of the training period didn't have much affect on it. Thus, it was assumed the convergence state of the map to be reached. No analysis on neighborhood preservation was performed on the trained map.

6.4.4 Network calibration

As discussed earlier a fingerprint utility information was used for trained SOM network labeling. Steps taken for network calibration can be summarized as follows:

- Utility score assignment for each fingerprint sample of training data set.
- Presentation of fingerprint samples with assigned utility information to the trained network and determination of winner neurons for each of the samples.

- Assignment of utility information from samples to the corresponding winner neurons.

In the cases when a neuron on the map was activated by more than one sample, utility scores for the neuron where collected in the list. For the maps, where the number of neurons was much lower than the number of used in network training samples, the size of such list could we quite large. For that reason it was necessary to decide how to interpret such labeling information. Different strategies were considered for combining of utility scores assigned to neurons:

- *Winner-Takes-it-All (WTA).* This strategy included histogram calculation on all the label values of the neuron. Score with the highest histogram value was taken as a class label for the neuron. Thus, all the samples activating this neuron were considered as belonging to the cluster of fingerprint images with utility value of that class.

  Several variations of this strategy were considered for analysis of predictive capabilities of SOM network. These variations included taking the mean over the number of utility classes with the highest histogram value.

- *Mean.* This strategy included arithmetic mean value estimation from all label scores and considering resulting value as an utility class for the neuron. Ceiling function was applied to every mean value to map it to the smallest following integer.

For the maps, where the number of neurons was the same or larger than the number of used in network training samples, the situation could be faced when map would contain neurons not activated by any of the samples. As the labeling of the neurons is performed using samples of the training data set, such redundant neurons would not be labeled. On the other hand such neurons could be still activated by the samples of validation set. This would result in inability of SOM network to classify such samples. To overcome this possible problem the network calibration procedure was modified to search winner neurons only among those neurons in the map that were assigned labels.

6.5 Network validation

Validation is a critical aspect of any model construction. There is no well formulated or theoretical methodology for neural network model validation, but the usual practice is to base model validation upon some specified network performance measure of data that was not used in model construction [TS96].

For validation of SOM approach a data from constructed validation set was used. First, each of the samples from validation data set was mapped to utility values derived from comparison scores of these samples. These values will be referred as *observation* data. After that each of the samples was classified by trained SOM network and assigned an utility value. Results of SOM classification will be referred as *prediction* data.

In order to test performance of the proposed SOM based fingerprint quality estimation approach a number of tasks was identified:

- Evaluate classification accuracy of proposed approach.
- Compare quality estimation results of proposed approach with already existing methods for fingerprint quality assessment.
- Evaluate quality estimation results of proposed approach in terms of the affect of these results on biometric performance of the system.

For accomplishment of mentioned tasks a number of methods was selected. A brief discussion of these methods and used analysis methodology is provided in following sections.

6.5.1 Classification accuracy analysis

Two classification performance measures were selected for this analysis: mean squared error (MSE) and percent of good (PG) classification.

The definitions of MSE and PG measures are given in equations 6.2 and 6.3

$$MSE = \frac{\sum_{i=1}^{n}(p_i - o_i)^2}{n} \tag{6.2}$$

where p_i and o_i represent predicted and observed utility values for i^{th} sample accordingly.

$$PG = \frac{100}{n}\sum_{i=1}^{n} C \tag{6.3}$$

where

$$C = \begin{cases} 1 & \text{if } p_i - o_i = 0 \\ 0 & \text{otherwise} \end{cases} \tag{6.4}$$

where p_i and o_i represent predicted and observed utility values for i^{th} sample accordingly. Condition defined by equation 6.4 was sufficient to be used for utility scores defined in the range [1,10], but was to strict for utility values defined in the range [1,100]. Because of used interpretive schedules defined in section 6.4.4 and because of SOM nature to approximate probability density function of data sets, only approximate classification results could be expected for classification of fingerprint patterns. For larger scale of utility values the condition in 6.4 was changed as follows:

$$C = \begin{cases} 1 & \text{if } |p_i - o_i| \leq 10 \\ 0 & \text{otherwise} \end{cases} \tag{6.5}$$

6.5.2 Spearman correlation based analysis

In statistics, *Spearman's rank correlation coefficient* or *Spearman's rho*, named after Charles Spearman who first proposed this method in [Spe04]. It is a non-parametric measure of statistical dependence between two variables. It assesses how well the relationship between two variables can be described using a monotonic function. A perfect Spearman correlation of +1 or -1 occurs when relation between two variables are described by perfect monotone function. The Spearman correlation coefficient is defined by equation

$$\rho = \frac{\sum_i (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_i (x_i - \overline{x})^2 \sum_i (y_i - \overline{y})^2}} \tag{6.6}$$

Correlation coefficient between observed and predicted utility values was used as a method performance measure in comparison with existing fingerprint quality estimation approaches.

Chapter 7

Experimental Results

Previous chapters described the concept of fingerprint quality estimation and a novel quality assessment approach based on Self-Organizing Maps algorithm. In this chapter experimental results of analysis of proposed approach are presented and analyzed. Many different experiments were conducted during the project and in this chapter only those experiments and their results are covered, which we believe let us prove the concept of fingerprint quality assessment using Self-Organizing maps.

7.1 Clustering of fingerprint patterns using SOM

As it was discussed in previous chapter, on the first stage of the project it was important to see if it is possible to train the SOM network so it could recognize different classes of fingerprint images and find out what kind of fingerprint image data would be most suitable for network training. For that purpose several experiments were conducted constructing feature vectors using raw image data as discussed in section 6.4.1.1. Two cases had been tested: performing preprocessing of fingerprint images as discussed in section 6.3.2 and constructing feature vectors without any prior preprocessing. Constructed feature vectors were used in training of SOM network with competitive layer of rectangular topology and the size of 64x64 neurons. For all experiments on this stage the training was performed using one training phase with initial learning rate 0.5, initial neighborhood distance 16 and training length equal to 100000 iterations.

For visual analysis of the trained map an *Unified distance matrix* (U-Matrix) approach was used. In this method average distances between neighboring codebook vectors are represented by shades in a gray-scale. If the average distance of neighboring codebook vector is small, a light shade is used; and vice versa, dark shades represent large distances, thus clearly visualizing the classification of a "cluster landscape" formed over the SOM [Koh01].

After the training of SOM networks, their corresponding u-matrices were generated. On each of the matrices a number of groups of locally placed neurons, was manually identified to analyze what kind of images were recognized by the cluster. Clusters were selected in different areas of the map in order to check topological ordering of information by the map. Figure 7.1 illustrates the u-matrix for SOM trained with raw data feature vectors. Selected clusters are marked with red rectangles and labeled with an integer for each of the three clusters. Figure 7.2 shows a randomly selected subset of images from each of the three clusters. Accordingly, figures 7.3 and 7.4 illustrate clustering results for SOM network trained with preprocessed data. Visual analysis of images in selected clusters shows that there is a great similarity among images of each particular cluster. Moreover it can be seen that neurons in different parts of the map that are located far away from each other are reacting on different image patterns, whereas close to each other neurons are reacting on similar patterns. This proves the topological ordering of image pattern information by SOM network.

Discussed experimental results showed that selected feature construction methods were suitable for futher usage in SOM based fingerprint quality assessment method.

7.2 Analysis of SOM clustered patterns

In the next set of experiments the goal was to analyze how fingerprint images which have been recognized by the same neuron in the map are similar in terms of their quality. If SOM provided a good grouping of patterns by their quality, labels assigned to each of the neurons in the map after calibration process would lay in a small range of values. In order to check this assumption we looked at a standard deviation of utility values assigned to each of the neurons. Low standard deviation among utility labels assigned to the neuron would mean

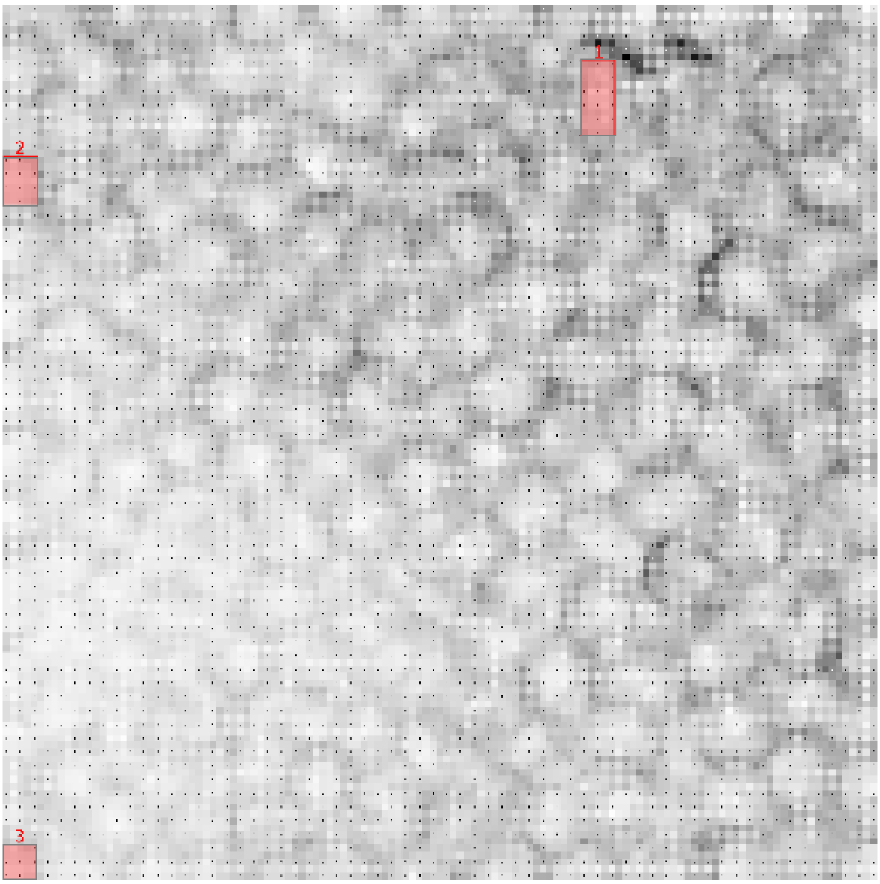
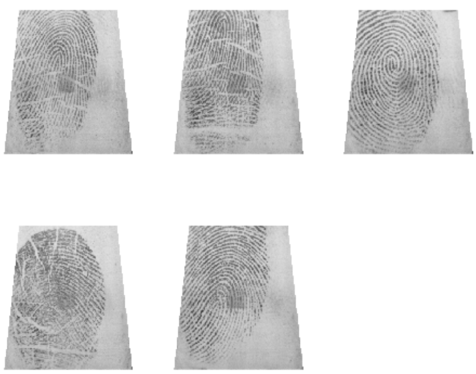


Figure 7.1: U-matrix of 64x64 size SOM trained with unsegmented data set

(a) group1

(b) group2



(c) group3

Figure 7.2: Fingerprint images recognized by neurons in selected clusters

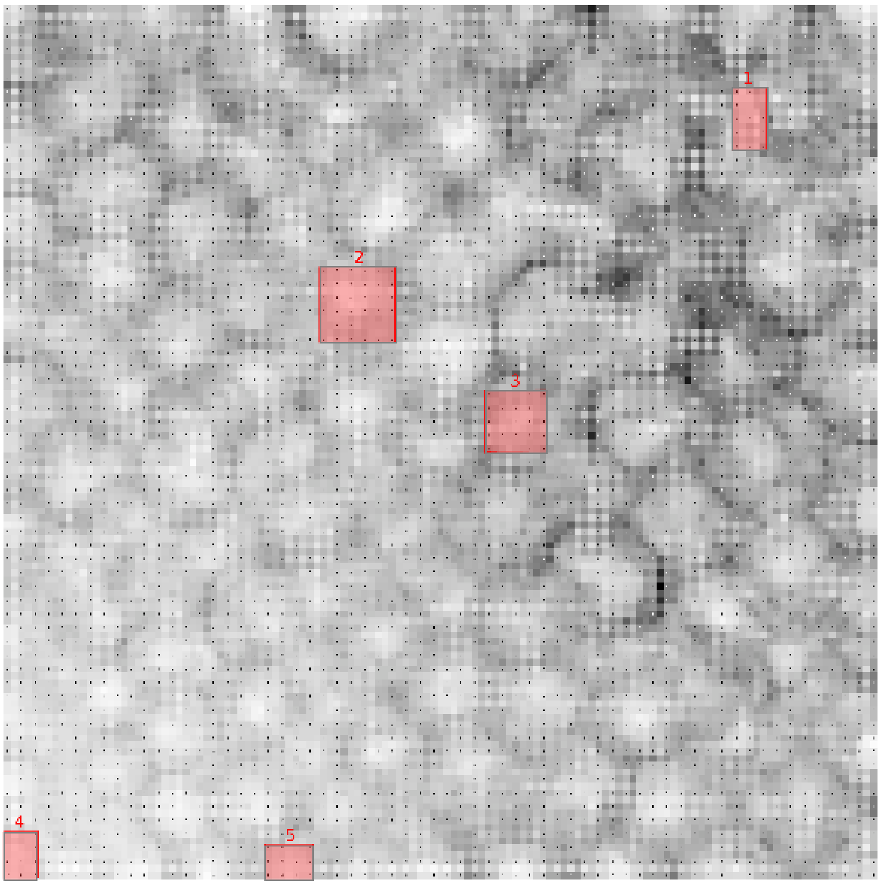
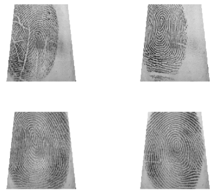


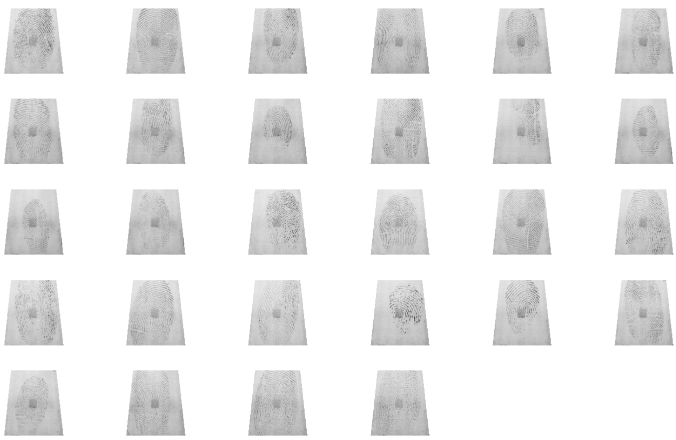
Figure 7.3: U-matrix of 64x64 size SOM trained with segmented data set

(a) group1

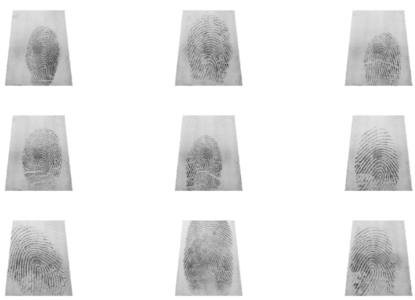


(b) group2

(c) group3



(d) group4



(e) group5

Figure 7.4: Fingerprint images recognized by neurons in selected clusters

that this neuron is activated by similar patterns and thus this would prove SOM capabilities to distinguish different classes of fingerprint quality.

On this stage experiments were conducted by training SOM networks with hexagonal topology of neurons in competitive layer of size 64x64 with raw data feature vectors. CASIAFPv5 data set was used for experiments and preprocessing procedure was applied to each of the samples. Training was performed in two phases as discussed in section 6.4.3.1.

Figures 7.5, 7.6 and 7.7 show distribution of standard deviation values on the map for utility values of three different vendors. All standard deviation computations were performed on normalized to the range of [0,100] utility values. Results of analysis showed that for most of the neurons, which were assigned utility values of provider 28 the standard deviation was very small. It was showing that most of the neurons in such trained map were activated by the patterns with similar quality.

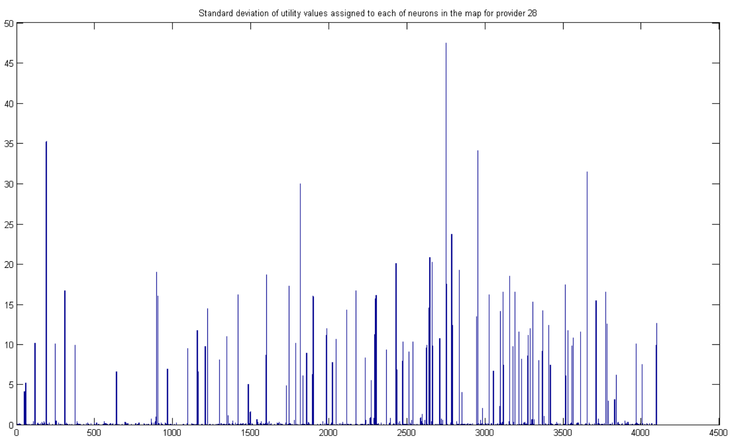


Figure 7.5: Standard deviation of assigned utility values of provider 28 to each neuron of the map

In another set of tests it was tried to look at the difference between predicted and observed utility values for each of the neurons in the map. The mean of all utility values assigned to each of the neurons was used as a predicted utility data. The difference between predicted and observed utility values for each of available vendors is shown in figures 7.8, 7.9 and 7.10. These tests also showed the best results for utility scores derived using comparison algorithm of vendor 28. This met our expectations because the comparison algorithm with id 28 was considered as providing the best fingerprint comparison results.

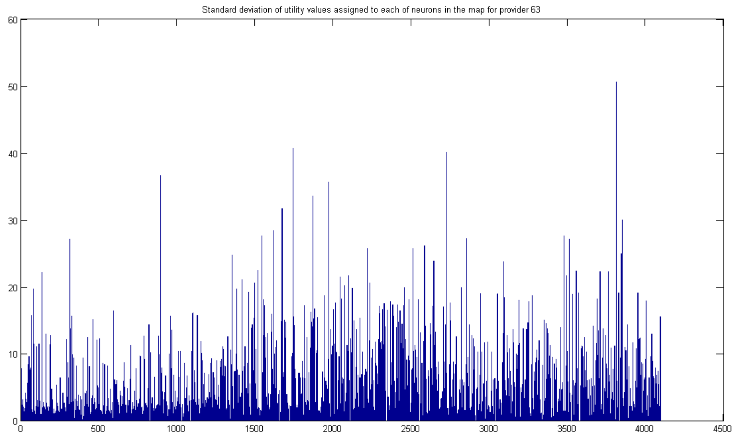


Figure 7.6: Standard deviation of assigned utility values of provider 63 to each neuron of the map

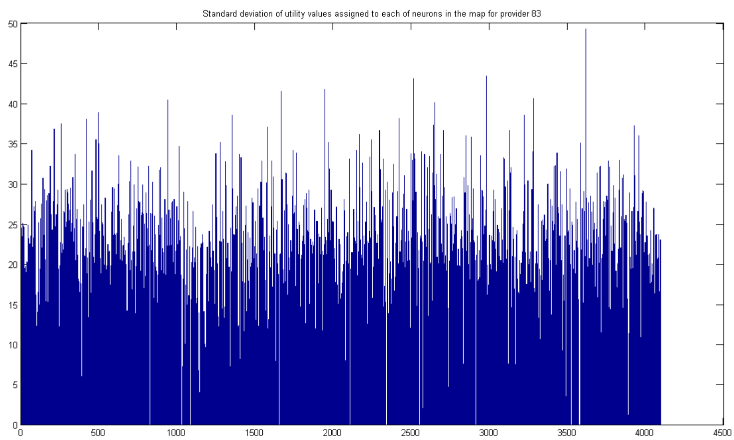


Figure 7.7: Standard deviation of assigned utility values of provider 83 to each neuron of the map

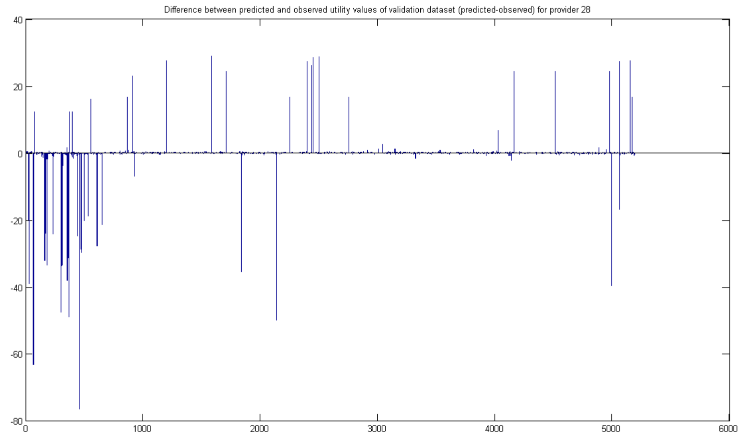


Figure 7.8: difference between observered and predicted utility values for provider 28 for validation data set

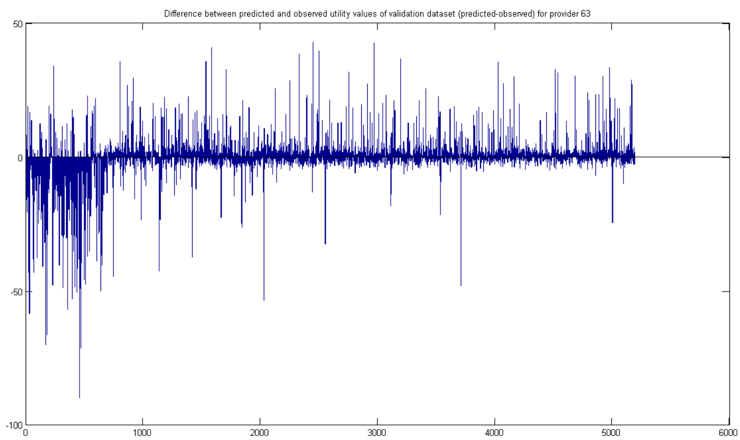


Figure 7.9: difference between observered and predicted utility values for provider 63 for validation data set

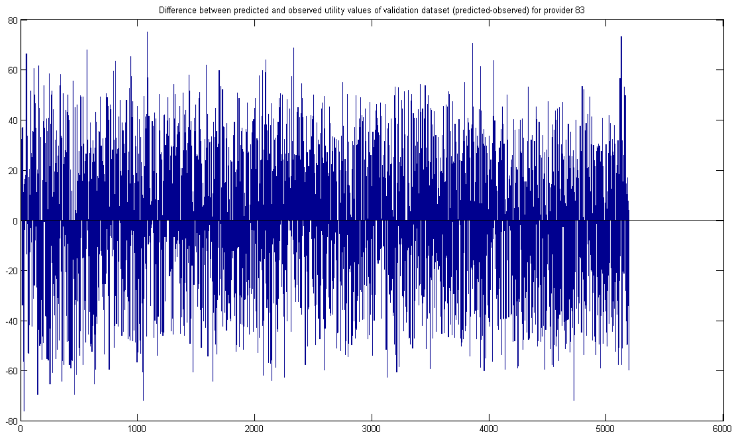


Figure 7.10: difference between observered and predicted utility values for provider 83 for validation data set

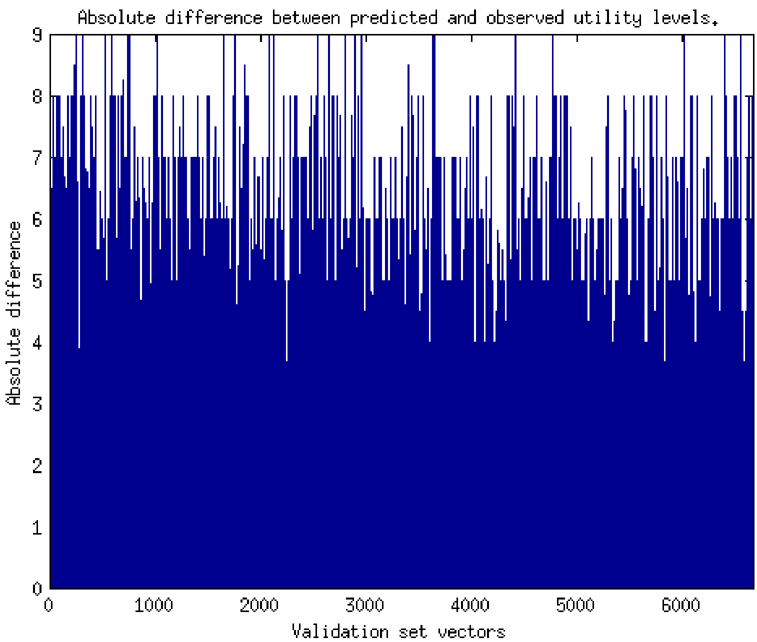


Figure 7.11: difference between observered and predicted fused utility values of prividers 28, 63, 83 for validation data set

On the other hand, by analyzing the distribution of observed utility values for the samples of training data set (fig. 7.12, 7.13, 7.14) for each of the vendors it was seen that most of utility scores for vendor 28 fell into the small range of values. This fact could explain small standard deviation and difference between observed and predicted values for that vendor. Because of that, results of tests performed using separate utility values of different vendors were considered as not sufficient to prove quality prediction capabilities of SOM network. Therefore, it was decided to conduct future experiments on fused utility values from three vendors and performing binning of utility scores with maintenance of uniform distribution of scores in the chosen utility scale. Final difference results on fused and binned to 10 classes utility scores are shown in figure 7.11. As can be seen from the figure, SOM classification error was remaining quite high for chosen configuration.

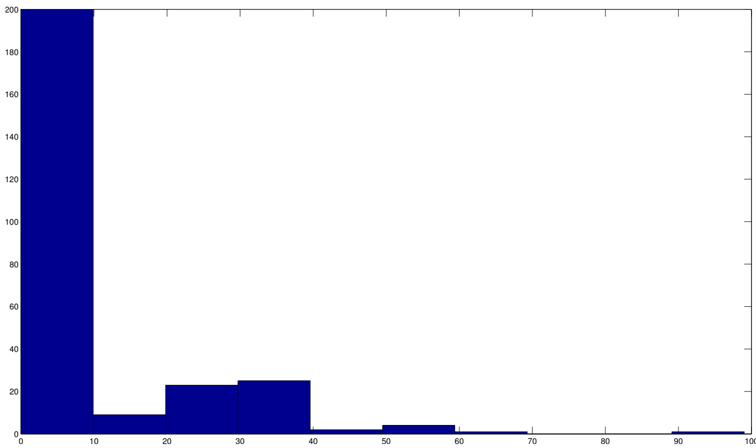


Figure 7.12: Distribution of utility scores for vendor 28. The vertical scale is intentionally limited for better visualisation of histogram.

7.3 SOM classification accuracy analysis

A number of tests was performed in order to analyze the accuracy of classification performed by SOM network on fingerprint using various configuration parameters. First, an effect of different strategies for fusion of utility scores, which were discussed in section 6.4.4, on classification accuracy was analyzed. Different variants of WTA utility score fusion approaches were chosen for study. In presented below results these approaches are referred as *WTA-1*, *WTA-2* and *WTA-3* according to the number of used winner labels for final class value estimation. Also, in this study different feature vector construction methods were

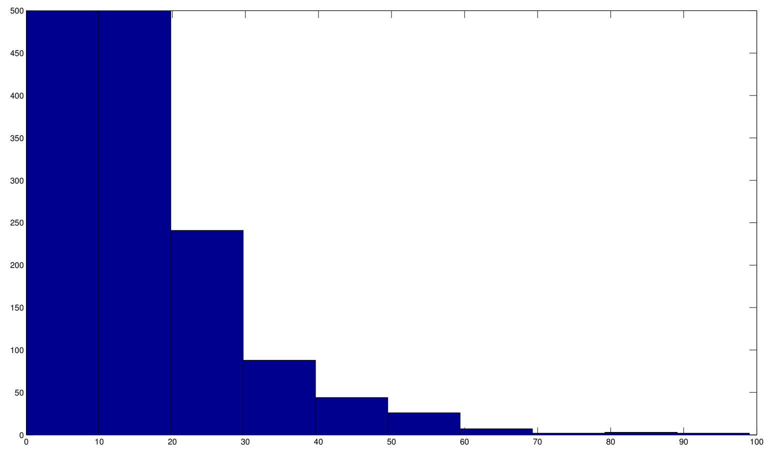


Figure 7.13: Distribution of utility scores for vendor 63. The vertical scale is intentionally limited for better visualization of histogram.

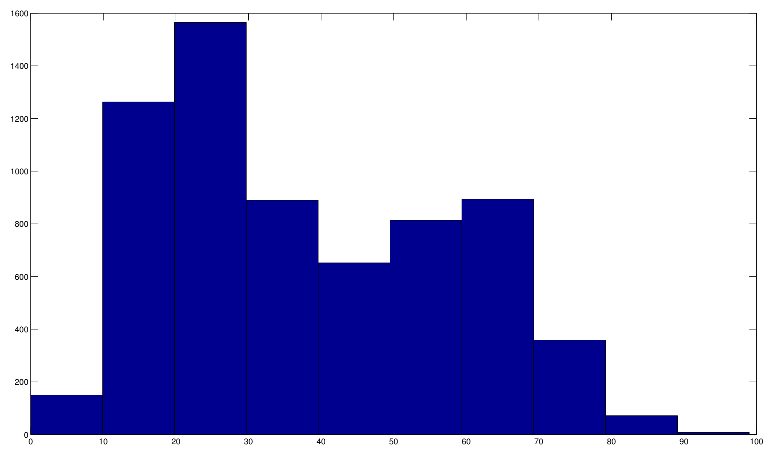


Figure 7.14: Distribution of utility scores for vendor 83

16x16, utility binned to 10 classes				
	WTA-1	WTA-2	WTA-3	Mean
Raw data				
Total Accuracy	12,84%	11,34%	11,29%	10,42%
Correlation	16,11	16,53	16,70	20,27
MSE	16,14	11,38	9,64	8,10
FFT				
Total Accuracy	12,64%	11,77%	10,51%	10,56%
Correlation	17,49	17,28	18,13	19,39
MSE	15,99	11,73	9,97	8,15

Table 7.1: Summarized performance results for different utility score fusion strategies

analyzed.

For the study a SOM network with hexagonal topology and size 16x16 of competitive layer was used. Calibration of network was performed on fused and binned to 10 classes utility values. Network training length was set to 500000 iterations.

Table 7.1 summarizes classification performance results for different fusion strategies. As can be seen from presented results, there is a tendency for performance to improve as larger number of winner labels is used for final class estimation. Therefore in later experiments a focus is made on usage of a Mean strategy for fusion of utility scores. Tables 7.2, 7.3, 7.4 and 7.5 present a more detailed classification accuracy estimation results. In each of the tables first row shows accuracy results estimated using PG metric defined in section 6.3 for each individual utility class. Values for this measure show a percent of validation set samples that were assigned the utility value that was equal to the one, estimated from comparison scores of the samples.the Second row shows total accuracy results for the whole data set.

One of the tested methods included preprocessing of fingerprint images before feature construction. In this method pixels of the fingerprint image, which were assigned to the background, were marked as missing data. The idea behind this approach was to speedup SOM network training as missing components of feature vectors would be ignored in distance computation. As can be seen from the results this feature vector construction approach gave worst results among all tested approaches. For later experiments this approach was changed by assigning to background pixels a white color value. In further discussion of this chapter this approach is referred as *white segmentation*.

16x16, utility binned to 10 classes				
	Quality class	Raw data	Preprocessed data	FFT
Accuracy	1	25,54%	20,43%	27,86%
	2	9,83%	12,86%	10,74%
	3	10,17%	10,17%	6,22%
	4	3,56%	5,93%	8,61%
	5	5,13%	8,80%	6,60%
	6	8,88%	7,42%	5,53%
	7	12,74%	7,53%	5,93%
	8	6,89%	10,33%	8,68%
	9	8,57%	6,07%	14,17%
	10	38,05%	17,05%	33,49%
Total Accuracy		12,84%	10,60%	12,64%
Correlation		16,11	6,96	17,49

Table 7.2: Quality prediction results for 6666 tested samples using WTA-1 approach

Table 7.6 shows results of accuracy analysis for the network of size 16x16 neurons. In this analysis utility values binned to 100 classes were used for network calibration. Utility class for each of the neurons was derived using *Mean* approach, as this approach showed the best results in previous experiments. Also, as previous experiments showed good results for feature vectors construction approach where raw image data was used, in this study the intention was to see how reduction of image area which was used for feature vector construction would affect classification results. For that purpose feature vectors were constructed

16x16, utility binned to 10 classes				
	Quality class	Raw data	Preprocessed data	FFT
Accuracy	1	10,06%	6,66%	8,05%
	2	7,41%	11,50%	15,43%
	3	11,53%	8,50%	17,15%
	4	16,02%	14,99%	9,20%
	5	19,65%	17,45%	16,57%
	6	13,25%	17,76%	10,19%
	7	6,66%	14,33%	13,02%
	8	14,97%	6,59%	14,97%
	9	13,55%	9,50%	12,93%
	10	0%	0%	0%
Total Accuracy		11,34%	10,81%	11,77%
Correlation		16,53	9,20	17,28

Table 7.3: Quality prediction results for 6666 tested samples using WTA-2 approach

16x16, utility binned to 10 classes				
	Quality class	Raw data	Preprocessed data	FFT
Accuracy	1	0%	0%	0%
	2	7,11%	6,20%	8,02%
	3	12,44%	9,86%	10,02%
	4	25,96%	16,47%	22,85%
	5	19,21%	24,93%	20,38%
	6	23,29%	22,56%	18,63%
	7	10,13%	13,60%	16,50%
	8	7,93%	8,98%	7,04%
	9	5,45%	1,25%	0%
	10	0%	0%	0%
Total Accuracy		11,29%	10,56%	10,51%
Correlation		16,70	8,59	18,13

Table 7.4: Quality prediction results for 6666 tested samples using WTA-3 approach

16x16, utility binned to 10 classes				
	Quality class	Raw data	Preprocessed data	FFT
Accuracy	1	0%	0%	0%
	2	0%	0%	0%
	3	3,79%	0,76%	2,43%
	4	24,63%	19,58%	30,86%
	5	47,51%	61,88%	39,74%
	6	23,29%	20,38%	26,78%
	7	2,89%	0,14%	3,62%
	8	0%	0%	0%
	9	0%	0%	0%
	10	0%	0%	0%
Total Accuracy		10,42%	10,50%	10,56%
Correlation		20,27	9,10	19,39

Table 7.5: Quality prediction results for 6666 tested samples using Mean approach

16x16, utility binned to 100 classes					
	Raw-1	Raw-2	Raw-3	White segment.	FFT
Total Accuracy	21,15%	21,57%	22,18%	24,57%	20,89%
Correlation	21,81	20,91	20,17	17,96	21,48
MSE	781,12	783,27	784,34	676,26	781,03

Table 7.6: Quality prediction results for 6666 tested samples using Mean approach

using cropped areas of different sizes of fingerprint image. Tested fingerprint areas centered o fingerprint pattern in the image included sizes: 356x328 pixels (Raw-1), 240x240 pixels (Raw-2) and 160x160 pixels (Raw-3). As can be seen from the results reduction of the size of fingerprint image didn't have any affect on classification results and for each of the tested approaches analysis results were practically the same.

Further analysis of classification results of SOM network constructed using Raw-1 approach was performed. Figure 7.15 shows the absolute difference between predicted and observed utility classes for each of the samples of validation data set and distribution of samples according to the size of classification error. As can be seen from the figure for most of the samples the difference between observed and predicted utility laid in the range of [0,40].

To analyze predictive capabilities of SOM network samples of validation data set where divided into two classes representing two quality class (good and bad). First class contained images with predicted by SOM utility scores less than 50 and second class contained images with predicted utility scores above 50. Next for each from the samples of each class a histogram was build using observed utility scores of samples in the set. If histograms would show that in the group containing images with predicted bad quality there are more samples with observed bad quality and the same would apply for the group with samples of a good quality, it would prove SOM capabilities to predict fingerprint quality. The results of such analysis for Raw-1 approach are shown in figure 7.16. For a good quality assessment it would be desirable to have very large difference in size of two columns of given histograms.

7.4 Impact of competitive layer's size on the accuracy of quality assessment

SOM network can be seen as a model for human brains 'associative memory' [Koh01]. Therefore, intuitively it can be assumed that an increase in the size of the map can lead to an increase in capabilities of the map to discriminate more data classes and thus to a better clustering of signals. To check this assumption SOM networks of different sizes were trained using fingerprint images and quality assessment accuracy was tested on each of the maps.

In this study maps of eight sizes were constructed: 8x8, 16x16, 24x24, 32x32, 40x40, 48x48, 56x56 and 64x64. For each of the maps hexagonal topology of neurons was chosen. The training was performed in two phases using 1000000 training iterations in total. Maps were trained using *white segmentation* ap-

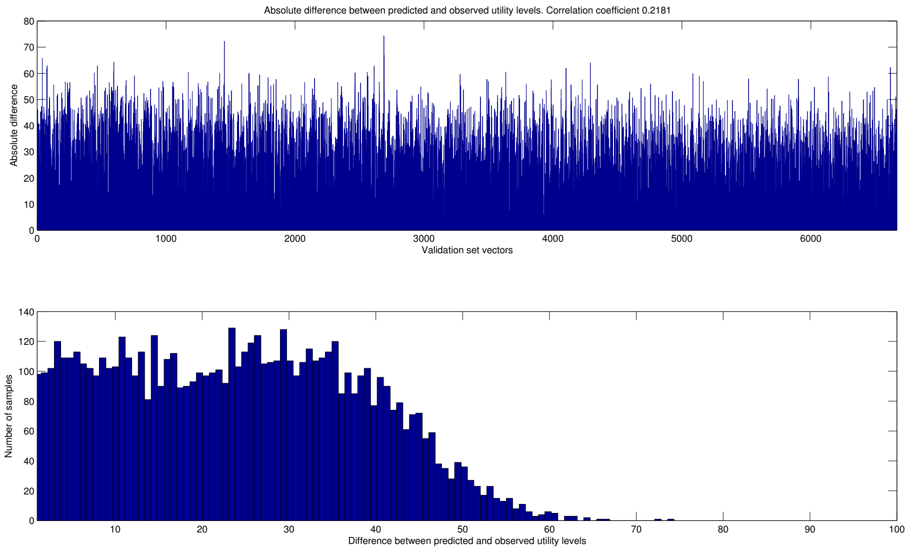


Figure 7.15: Classification histograms for Raw-1 approach

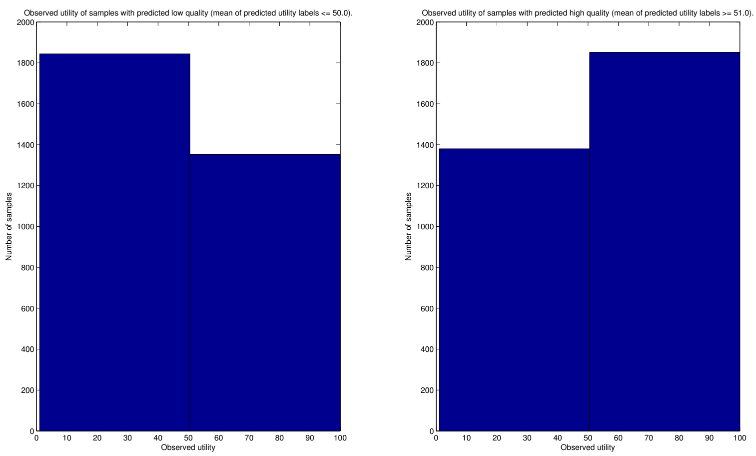
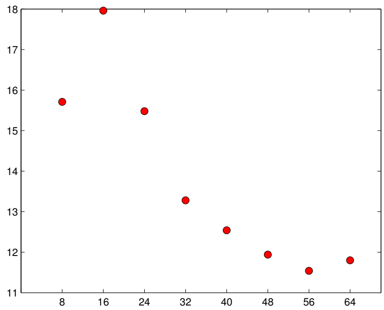
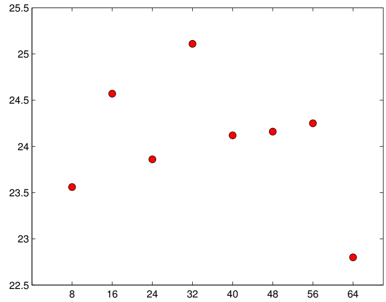


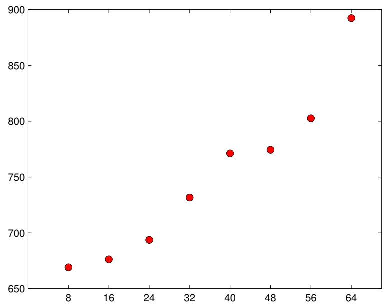
Figure 7.16: Classification histograms for Raw-1 approach. Left figure: histogram for samples with low predicted utility. Right figure: histogram for samples with high predicted utility



(a) Spearman correlation



(b) Percent of correct classifications



(c) Mean squared error

Figure 7.17: Classification performance according to the size of the map

proach for feature vector construction and *Mean* approach for estimation of class values after calibration process. Network calibration was performed using fused utility values binned to 100 classes.

In figure 7.17 results of this analysis are presented. As can be seen the best classification accuracy was achieved on the map of the size 16x16 neurons.

7.5 Comparison with existing quality metrics

Spearman correlation was used to compare results of SOM based quality estimation approach with the results of existing approaches. For that purpose quality scores of all available quality metrics were derived for the samples of validation data set and for each pare of quality estimation method Spearman correlation coefficient was calculated. Resulting correlation matrix for is shown in figure 7.18.

In this analysis several SOM classifiers were constructed using 16x16 network with hexagonal topology of neurons and using different features construction methods. For network calibration fused and binned to 100 classes utility values were used.

As it can be seen such quality estimation approaches as NFIQ, OCL or LCS don't produce fingerprint quality prediction results that would have very high correlation with observed utility scores (last column). This puts the proposed SOM quality estimation approach on the same level with these methods. Moreover, SOM based approach by correlation values overcome most of the tested methods.

	raw.1	raw.2	raw.3	fft	fda	gabor	gs	lcs	ocl	of	pow	rvu	nfiq	utility_bin
raw.1	100	62	60	26	−33	49	48	47	38	32	46	−44	−44	22
raw.2	62	100	66	24	−32	47	48	45	34	34	42	−42	−41	21
raw.3	60	66	100	24	−30	47	47	44	32	32	43	−41	−40	20
fft	26	24	24	100	−12	17	17	14	33	7	24	−27	−35	21
fda	−33	−32	−30	−12	100	−53	−55	−50	−33	−41	−35	46	40	−14
gabor	49	47	47	17	−53	100	65	81	63	47	75	−53	−61	22
gs	48	48	47	17	−55	65	100	65	36	52	53	−56	−49	17
lcs	47	45	44	14	−50	81	65	100	58	50	63	−51	−56	20
ocl	38	34	32	33	−33	63	36	58	100	35	48	−39	−63	26
of	32	34	32	7	−41	47	52	50	35	100	23	−47	−40	15
pow	46	42	43	24	−35	75	53	63	48	23	100	−44	−49	24
rvu	−44	−42	−41	−27	46	−53	−56	−51	−39	−47	−44	100	48	−20
nfiq	−44	−41	−40	−35	40	−61	−49	−56	−63	−40	−49	48	100	−27
utility_bin	22	21	20	21	−14	22	17	20	26	15	24	−20	−27	100

Figure 7.18: Correlation matrix for fingerprint quality assessment metrics

Presented in this chapter experimental results show are considered as proving the ability of SOM network to predict the quality of fingerprint samples in relation with biometric performance. As it was the first study on SOM application for fingerprint quality assessment during which only few configuration sets were tested, there is a high probability that in future studies the performance of SOM approach will be improved.

Chapter 8

Processing speed analysis

Experimental results show that the process of SOM network training, when highly dimensional data vectors are used, is computationally intensive and resource demanding. Depending on chosen map and training configuration the time required for construction of the model could require more than one day and this was a limiting factor for the analysis of a larger number of configuration sets. As a construction of SOM based fingerprint quality assessment model is performed offline, the time needed for model construction is not of so importance. On the other hand for real-time quality assessment the response time of the algorithm plays a crucial role and for that reason a thorough analysis of processing speed of the algorithm must be made before it will be used in production mode. In this chapter a processing speed of proposed SOM based fingerprint quality assessment method is analyzed and a discussion provided on the ways of improving this speed.

8.1 Current processing speed of SOM approach

A benchmark was performed in order to estimate the time required for SOM network training as well as for processing of single fingerprint image by the trained network. For that purpose maps of three different sizes were trained:

Map size	Network training time	Image processing time	
		full set	single image
16x16	1150 min	600 sec	0,045 sec
32x32	3950 min	2080 sec	0,156 sec
64x64	12000 min	8500 sec	0,638 sec

Table 8.1: Processing time for SOM networks of different sizes

16x16, 32x32 and 64x64. For evaluation a standard two-phase training was used with the total length of 1000000 iterations. Feature vectors for SOM network training were constructed using *White segmentation* method. Tests were performed on computer with processor speed of 2.6GHz running the program in single-threaded mode.

Table 8.1 shows the processing times for SOM networks of different sizes. A training data set of 13333 fingerprint images was used in processing time estimation network training and single image processing. As it can be seen from the results, on all of the tested maps processing of a single fingerprint image required less than a second and for the map of size 16x16 that was showing best accuracy results in previous tests the processing of a single image took less than 0.1 second. This result was compared to the processing speed of NFIQ algorithm. For that purpose a quality estimation using NFIQ algorithm was performed for the same data set and on the same computer. A data set of 13333 images was processed by NFIQ algorithm in 1634 seconds which results in processing time of *0.122 seconds per image*. This result shows that SOM approach is faster, which makes this algorithm more attractive to be used in embedded systems.

8.2 Speed-up approaches

As can be seen from the results in table 8.1 the training of large maps with raw data feature vectors takes more than 5 days. For this project limited processing resources were available that let conduct training of one network at a time. Such a long training time was unacceptable and a number of attempts was made to make training of the SOM network with available data set perform faster.

As SOM network represents concurrent computational model where each of neurons act as separate processing units, intuitively the simple way of speeding up would be making SOM computations run concurrently on several computer processors. Analysis of programs in SOM_PAK software package showed that this SOM algorithm implementation was implemented to run on single processor only. At CASED two computers with 4 and 8 processing units were available for the project and if SOM computations run on all of these processing units, this could definitely reduce the training time.

Modern compilers can automatically adopt the program code to run on multiple processors. The first approach to introduce concurrency in SOM algorithm was to use this ability of compilers. Several C compilers were tested: GCC v 4.6, MinGW-w64, PGI. Unfortunately no significant increase in computational speed was achieved. On the other hand during the study it was seen that processor speed has direct impact on the training time. For example SOM training on available CASED server turned to be twice slower than on a desktop computer in the data bar. Even processors on the data bar computer had less cores, the speed of one core was faster comparing with the speed of processor cores on the server and for signle threaded applications of SOM_PAK it resulted in big processing time differences on these two machines.

Another considered speedup approach was rewriting part of the code of SOM_PAK programs in order to use several threads for program execution and explicitly identify areas of the program that need to be processed concurrently. Directives of OpenMP interface were used for paralleling of execution of programs. With this approach no significant increase in computational time was also achieved. Programs of current SOM implementation were written in order to be run in a single-threaded mode and making them run on several processors would require considerable amount of effort and time. Therefore, this kind of speedup approaches of SOM algorithm were left for future works.

By analyzing the SOM algorithm it was seen that the most time consuming part of the algorithm is the determination of the neuron in the competitive layer which is activated by a given input. It is the neuron whose codebook vector is the closest to the input vector in the selected feature space. As was discussed previously winner neuron in competitive layer of the network is determined by calculating the distances of each codebook vector to the given input and selecting the one with the least distance (equation 5.2). Assuming the number of neurons in the map equal to N, dimensionality of used feature vectors equal to M and Euclidean distance as a distance metric, the total number of arithmetic operations required for winner detection on the map can be approximately estimated as $3 * N * M$. Therefore, two approaches of computational complexity reduction of the algorithm are possible: reduction of feature vector dimensionality and reduction of neurons that need to be checked to determine the winner.

In discussed experiments the dimensionality reduction of feature vectors was implemented with *FFT* feature costruction method. Dimensionality reduction in feature vectors was also used in discussed feature vector constructioin methods where cropped area of the fingerprint image was used. All these approaches resulted in reduction of computational time and with *FFT* the reduction in network training time let train the network in minutes.

A more complex problem is the reduction of winner search operations in SOM algorithm. A number of methods has been proposed in the literature for optimization of SOM computations employing the mentioned concept [WBS94], [Koh01].

8.2.1 Shortcut winner search

In this section results of SOM algorithm optimization, implemented according to the suggested method in [Koh01], are discussed.

Suggested approach is intended for speeding up of the training process of SOM algorithm and steps of it can be summarized as follows:

1. In the middle of an iterative SOM training process, whereby the last winner corresponding to each training vector has been determined at an earlier cycle, linear table is constructed where mapping of each training sample to its winner neuron is stored.
2. In following iterations of the training process exhaustive winner search over the whole SOM is replaced by the search in vicinity old winner for the input vector. The search is first made in the immediate surround of the old winner location, and if the best match is found at the edge, searching is continued in the surround of the preliminary best match , until the winner location is one of the middle units in the search domain.
3. After winner neuron was found the record for the input vector in the winner table is updated with new coordinates of the winner neuron for that sample.

By implementing mentioned algorithm the benchmark of optimized SOM network was performed along with an analysis of its classification accuracy. Tables 8.2 and 8.3 show the training time and classification accuracy results for the optimized algorithm. Experimental results show that a significant increase in processing time of the algorithm was achieved without reduction of classification accuracy in resulting model.

Map size	Network training time
16x16	500 min
32x32	1600 min
64x64	5000 min

Table 8.2: Processing times for optimized SOM networks of different sizes

16x16, white segmentation			
	Correlation	PG	MSE
Optimized algorithm	15.38	23.63	671,19
Algorithm without optimization	17.96	24.57	676.26

Table 8.3: Accuracy results for optimized and unoptimized algorithms

CHAPTER 9

Directions For Future Works

Although a comprehensive study of SOM based fingerprint quality assessment was performed, it is only considered as a starting point for further investigations of possibilities to use Self-Organizing Maps for fingerprint quality assessment. In previous chapters of the report evidences, showing SOM capabilities to predict fingerprint quality in relation to biometric performance of the system, were presented and a SOM based quality assessment framework was defined. The major goal for future studies is seen in finding a proper configuration for this framework to achieve more accurate fingerprint quality assessment.

Looking at what haven't been done in this study, several directions for future works can be identified:

- *Usage of larger data sets for model training and validation.* As it was discussed, due to the computational problems faced during the project an analysis of SOM based fingerprint quality estimation was limited to the usage of only one relatively small data set containing images acquired with only one sensing technology. This made the analysis results of proposed quality estimation approach to be tuned to one specific type of images. Therefore it is desirable to analyze the model which would be trained on a larger data set and preferably would contain fingerprint images from different scanners. On the other hand, it would be quite interesting to see how SOM classifier trained on one particular type of images would be able to generalize quality predictions on other type of images.

- *Usage of different configuration sets for model construction.* In this project only a small number of configurations was used for construction of SOM classifier and even smaller number of used configuration parameters were analyzed in terms of their effect on the accuracy of the model. Therefore, a comprehensive analysis of SOM configuration parameters is needed for estimation of the best configuration for classifier construction.

  First, this would include analysis of different configuration parameters of SOM competitive layer. In this study experiments were performed only using SOM networks with a square form of competitive layer. On the other hand Kohonen in his book [Koh01, p. 159] discusses that in most cases a rectangular form of the layer is preferable as it lets the map better fit the probability density function of the input data. In general it is suggested to perform an analysis of the data, which will be used for model construction before actual construction of the model in order to estimate probability density function. One of the methods suggested for that is Sammon projection [Sam69] which represents a non-linear projection of highly dimensional data into lower space with keeping topological relations between data elements. Application of this method makes it possible to visualize the data and make decision on choice of desirable configuration for the map. Due to the limitation of available software tools it was not possible to perform suggested analysis on available data vectors and this task is left for future studies.

  Another aspect related to the SOM configuration that would require a proper analysis is the relation between size of competitive layer, size of data set used for SOM classifier construction and number of data classes that trained network should distinguish. If relation among three mentioned parameters is found this would simplify the construction of SOM classifiers as by knowing the size of available data and desired number of classes it would be easy to choose appropriate size of the network for classifier construction.

- *Optimization of feature vector construction methods.* In this study an emphasis was put on analysis of feature vector construction methods in which for vector components a raw image data was used. This approach was considered a computationally efficient as it would require only low complexity preprocessing steps for fingerprint images.On the other hand, chosen approaches posses low invariance to the rotation, scaling or transformation of the pattern which is a common case for fingerprint images. For example slight rotation of the fingerprint image could result in a big difference when feature vector derived from the same fingerprint image would be compared with feature vectors using Euclidean or any other distance metric. This could result in the case when feature vectors representing the same fingerprint pattern would be assigned to different data clusters on the map and as a result incorrectly classified.

High dimensionality of the feature vectors used in SOM classifier training is seen as a problem that could limit the applicability of the proposed fingerprint quality estimation method. The SOM network consisting of large number of neurons with associated high dimensional weight vectors would require very large amount of memory that would be unacceptable for the platforms with limited resources. Therefore, ways of dimension reduction in feature vectors need to be found. Several approaches of dimensionality reduction were covered in this report, but all of the discussed methods assumed a loss of information in fingerprint image without performing any analysis how this could affect the resulting classification results. Differently, an analysis of contribution of each individual component of feature vector on the overall cluster structure in the map suggested in [Koh01, p.169] could be beneficial in this case, as it would let reduce the number of components in the feature vector by dismissing those components of the vector that don't contribute much to the cluster structure and have low explanatory power.

Yet another configuration parameter of SOM networks that requires a considerable attention is the choice of the distance metric. As it was discussed earlier Euclidean distance metric was used throughout the whole project, but by usage of other metrics could bring better results in terms of convergence speed of the map and classification accuracy. According to [LLB04] usage of other dissimilarity measures in SOM models could lead to easier detection of cluster structures on the map. Therefore, an analysis of different distance metrics for SOM based fingerprint quality assessment model is seen as an important direction for future works.

- *Improved utility computations.* In the project it was focused on application of the utility computation method defined by ISO/IEC 29794-1-2009 [ISOa] standard. For a proper analysis of SOM quality assessment model it is desirable to check classification results with other proposed utility computation models. Also experiments in the project were performed by using utility scores of only three commercial fingerprint comparison algorithms. Extending the number of used algorithms and usage of proper strategies for fusion of utility scores could result in larger degree of generalization of quality assessment model and more accurate quality prediction results.

Analysis of new speedup approaches. In the project only one speed up method, intended to reduce the time needed for network training, was implemented and analyzed. Model training time usually is usually not important as the training process is performed offline, but implemented method demonstrated that with slight modifications of the original SOM algorithm, a considerable reduction of processing time can be achieved. Therefore, analysis of other speedup approaches, especially those, intended for reduction of processing time of trained model, is seen a top priority task for future studies.

Analysis of quality predictions in relation to biometric performance. Another important task which is considered for future studies of the SOM based quality assessment approach is to analyze how quality predictions done by this approach affect the biometric performance of the system. This can be done by analyzing Error versus Reject Curves (ERC) proposed in [GT07]. Due to computation problems this analysis was not performed during the project, but results of it would give a better understanding SOM based quality assessment of fingerprint images can improve the biometric performance of the system.

CHAPTER 10

Conclusions

In this thesis an overview of theoretical aspects related to fingerprint quality analysis was made along with the proposal of a novel approach for fingerprint quality estimation based on Self-Organizing Maps.

It has been shown in the report that Kohonen's Self-Organizing Map trained on a large data set of feature vectors, which are derived from fingerprint images, is able without any prior knowledge of data classes to perform topological ordering of presented fingerprint information and thus provide a mechanism for later classification of fingerprint images. This work provides a detailed description of the framework based on which SOM fingerprint image classifier can be constructed and later used for quality assessment of fingerprint samples in relation to their effect on the biometric performance of the system. The high level of customization of the given framework provides large possibilities for fine tuning of quality assessment method as well as for its analysis using different configuration sets. Unsupervised nature of SOM algorithm, differently from NFIQ algorithm, enables to use fingerprint utility information only for cluster detection and interpretation of topological ordering in the constructed classification model, but not for direct model construction. This makes the proposed approach more flexible for changes in fingerprint utility computations. Once SOM network has been trained, various cluster detection and calibration techniques can be applied to it without exhausting resource and time consuming network retraining.

The results of comprehensive analysis of the proposed fingerprint quality assessment approach let us believe that convincing evidence of SOM network capabilities to perform quality analysis of fingerprint images have been found. Experimental results show that although the quality prediction results of the given approach in relation to prediction of biometric performance remain not very high, these results are the same and in some cases are superior in comparison with similar fingerprint assessment approaches. Moreover, low complexity, high speed and fulfillment of the fingerprint quality assessment requirements defined in ISO/IEC standard 29794-1 make this approach a perfect candidate to be used in the devices with limited computational resources.

To the knowledge of the author, no previous studies of SOM application to predict biometric performance of fingerprint samples have been done. Therefore, results achieved in this study look very promising and make proposed approach very attractive for further investigations. One of the main goals for future studies of the SOM fingerprint quality estimation method would be the search of the ways to improve results of its biometric performance predictions. A more careful selection of features representing fingerprint, that possess invariance to the rotation, scaling and transformation of the pattern would help to achieve this goal.

Appendix A

Examples of fingerprint images classified by SOM network

In this appendix examples of fingerprint images which were classified by SOM networks as having good or bad quality. SOM classifiers were constructed using different features of fingerprint images. Presented fingerprint images were selected by first selecting neurons with label class value higher or lower that set threshold representing good or bad quality of images accordingly. After needed neurons on the map are found, fingerprint images that activate chose neurons are selected. For all presented fingerprint images a preprocessing procedure was applied to derive statistical information from segmented pattern.

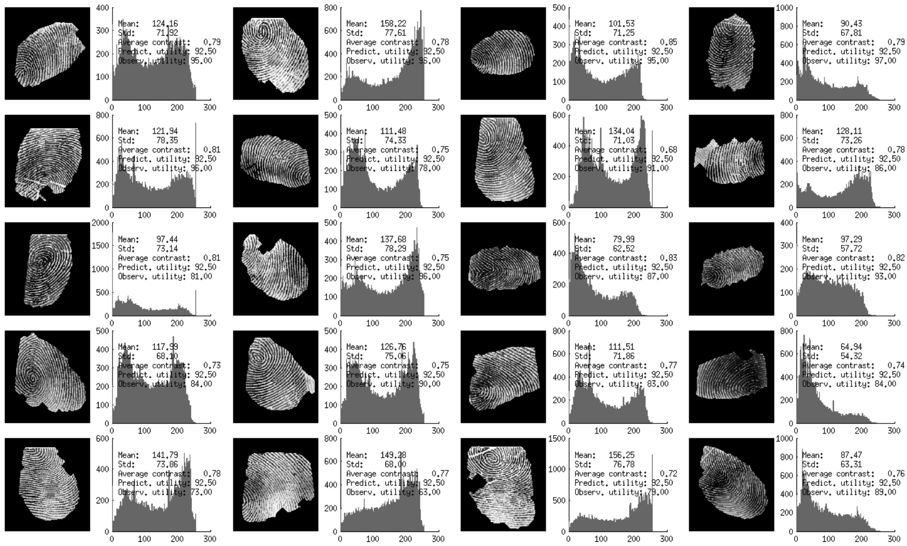


Figure A.1: Images considered by SOM network of size 16x16 trained using raw image data as having good quality. Threshold for predicted utility set to 90.

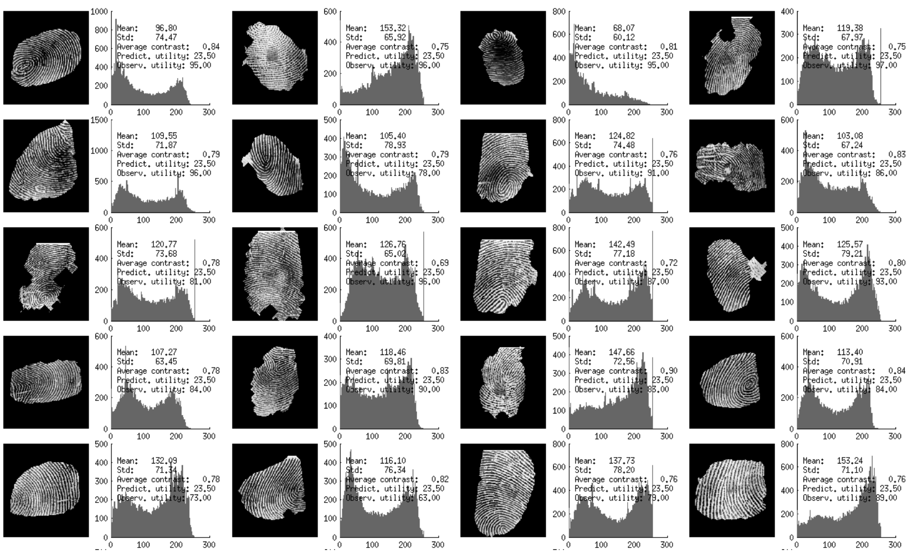


Figure A.2: Images considered by SOM network of size 16x16 trained using raw image data as having bad quality. Threshold for predicted utility set to 25.

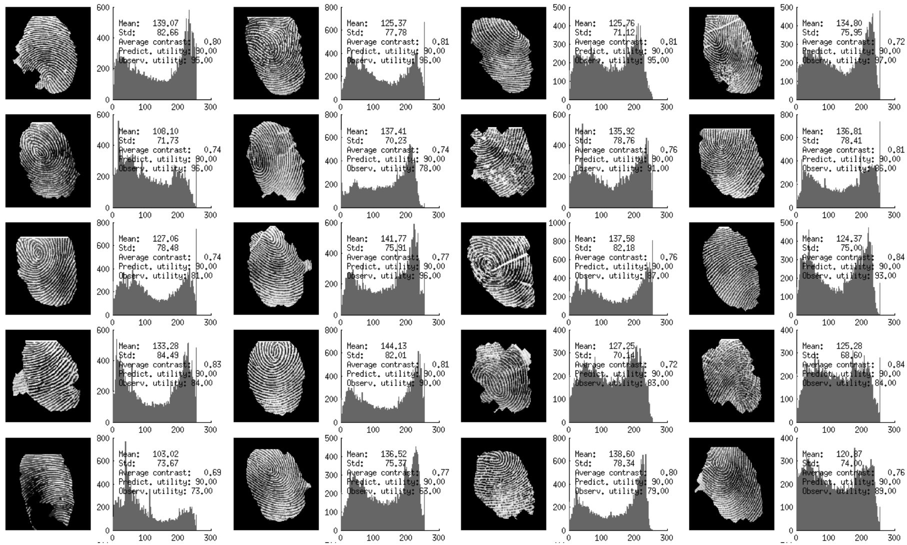


Figure A.3: Images considered by SOM network of size 16x16 trained using *white segmentation* feature vectors as having good quality. Threshold for predicted utility set to 90.

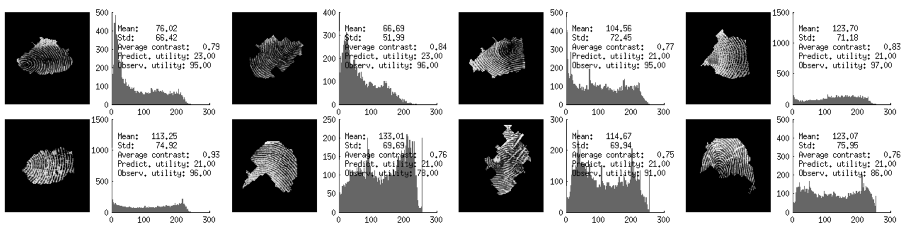


Figure A.4: Images considered by SOM network of size 16x16 trained using *white segmentation* feature vectors as having bad quality. Threshold for predicted utility set to 25.

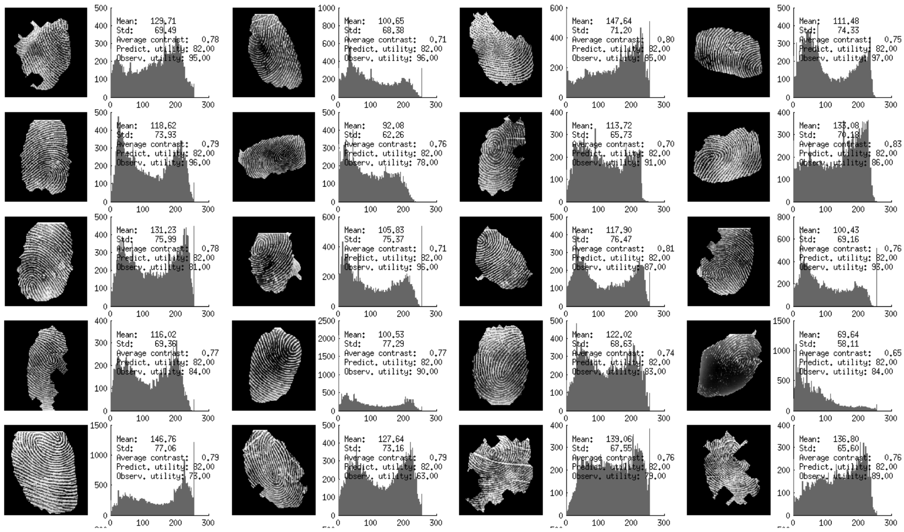


Figure A.5: Images considered by SOM network of size 16x16 trained using *FFT* feature vectors as having good quality. Threshold for predicted utility set to 80.

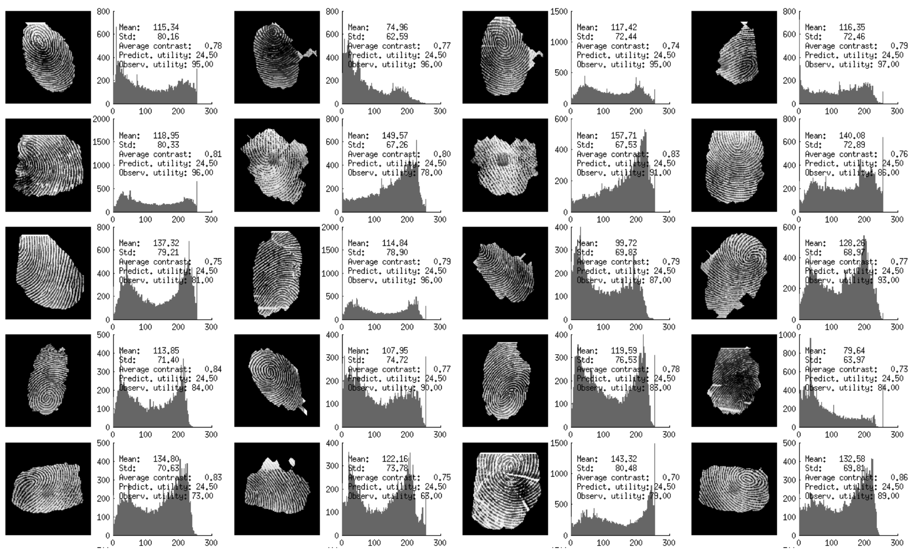


Figure A.6: Images considered by SOM network of size 16x16 trained using *FFT* feature vectors as having bad quality. Threshold for predicted utility set to 25.

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